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Modeling Army Applicants' Job Choices: The Enlisted Personnel Allocation System (EPAS) Simulation Job Choice Model (JCM)

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14. ABSTRACT *(Maximum 200 words)*: To ensure that the EPAS Field Test Simulation provides a realistic and unbiased evaluation of the optimization potential of EPAS, a model simulating Army applicants' job choice decisions is needed. This report summarizes development and evaluation of an empirically-grounded Job Choice Model (JCM), which relates applicants' aptitude scores, demographic characteristics, and job opportunity attributes (including monetary incentives) to their actual choices. As with real-world applicant decisions, it will be possible under the JCM for a given applicant to decide not to join the Army (not access). Similarly, if the applicant elects to join the Army (access), the JCM can simulate the applicant's choice of one of the many MOS reception-station date (job) opportunities from their job list. By sequentially modeling actual applicants' choice behavior, the JCM provides a realistic approximation of applicants' decision-making processes for simulation purposes. Evaluation of the JCM demonstrates that the model effectively simulates applicants' job choice decisions.

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MODELING ARMY APPLICANTS' JOB CHOICES: THE ENLISTED PERSONNEL ALLOCATION SYSTEM (EPAS) SIMULATION JOB CHOICE MODEL (JCM)

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INTRODUCTION

The Enlisted Personnel Allocation System (EPAS) is a classification optimization model that is designed to improve the efficiency of the matching process that links recruits to specific job training. The model was developed to work within the existing Army training reservation system, known as REQUEST. In lieu of a live field test of an EPAS-enhanced REQUEST system, we have developed a simulation field test to estimate the classification gains of the EPAS enhancement.

To ensure that the EPAS Field Test Simulation provides a realistic and unbiased evaluation of the optimization potential of EPAS, a model simulating Army applicants' job choice decisions is needed. This report summarizes our development and evaluation of an empirically-grounded Job Choice Model (JCM), which relates applicants' aptitude scores, demographic characteristics, and job opportunity attributes (including monetary incentives) to their actual choices. As with real-world applicant decisions, it will be possible under the JCM for a given applicant to decide not to join the Army (not access). Similarly, if the applicant elects to join the Army (access), the JCM can simulate the applicant's choice of one of the many MOS-reception-station date (job) opportunities from their job list.[1] By sequentially modeling actual applicants' choice behavior, the JCM provides a realistic approximation of applicants' decision-making processes for simulation purposes. Evaluation of the JCM demonstrates that the model effectively simulates applicants' job choice decisions.

This report is organized as follows. First, we summarize the JCM and our approach for mathematically estimating major components of the model, particularly applicants' preferences (or utilities) for different job opportunities. Second, the procedure employed for estimating the JCM is described and results evaluating the model's accuracy are presented. Third, and finally, the steps required to simulate applicants' job choices for purposes of implementing the JCM in the EPAS Simulation are documented.

MODELING ARMY APPLICANTS' JOB CHOICES

The main goal of the JCM is to statistically model applicant and job choice characteristics for purposes of simulating applicant job choice decisions in the EPAS Field Test. Conceptually, the JCM relates attributes of alternative job opportunities and characteristics of applicants to actual choices. Figure 1 summarizes the JCM and the attributes included in the model.

As evident from Figure 1, the JCM posits that Army applicants' job-choice decisions are a function of their preferences or utilities associated with the different job opportunities presented. These preferences are related to: (1) characteristics of the applicant (i.e., gender, education level, cognitive aptitude, etc.); (2) attributes of the available job opportunities (i.e., monetary incentives, rank order, etc.); and (3) the guidance counselor processing the applicant.

[1] For simulation purposes, it is possible for individuals in the applicant data who *actually did not join* the Army to *access* and be assigned an MOS. Conversely, it is also possible for individuals who *actually joined* the Army to *not access* during simulation runs. This is because the simulation models a random component of applicants' job choice decisions, which across multiple decision events would function to produce different choice decisions. Note that doing so increases rather than decreases the accuracy of the JCM for modeling real-world applicant choice decisions. More importantly, it ensures an accurate, unbiased evaluation of the optimization potential of EPAS.

Consistent with the actual decision-making process, the JCM produces a model of applicants' choices sequentially, starting with their decision to join (or not join) the Army followed by their choice of specific job opportunity from the list of those presented at time of enlistment.

While data on applicant and job opportunity attributes and applicants' actual job choices were available, applicants' preferences or utilities are latent (or unobserved) variables. To model these preferences, we applied discrete choice modeling and random utility theory. These modeling approaches have been widely used in econometrics to model consumer choice behavior (Greene, 1990) and, of particular relevance, in applied psychology to model Army enlistment and reenlistment behavior (e.g., Asch & Karoly, 1993; Hogan, Espinosa, Mackin, & Greenston, 2002).

The rest of this first part of the report is organized as follows. First, we present a general overview of the discrete choice and random utility framework underlying the JCM. Second, we develop this general framework to explain how we modeled the utilities applicants associated with different MOS training opportunities. Third, we present the full form of the JCM for predicting applicants' job choices based on these utilities.

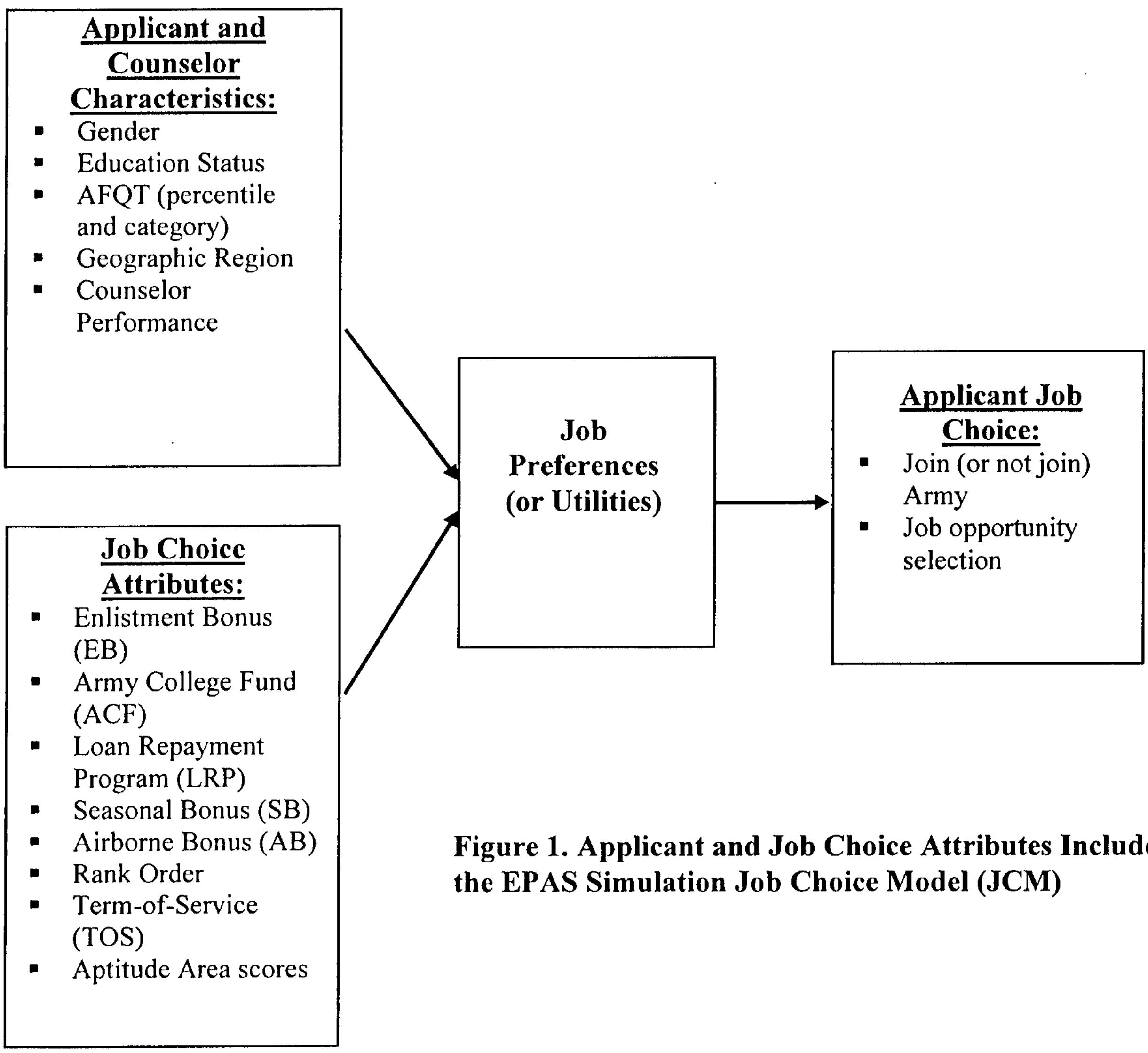

Figure 1. Applicant and Job Choice Attributes Included in the EPAS Simulation Job Choice Model (JCM)

Overview of the Modeling Framework

Our main motivation in developing the JCM was to construct a mathematical model that closely approximated the actual, real-world job choice process of Army applicants. Operationally, an applicant typically goes through a round of preliminary processing at the MEPS, then sits down with an Army guidance counselor to determine his/her MOS assignment. The counselor presents the applicant with a number of MOS training opportunities for which he/she is eligible based on test scores, demographics, and other criteria (e.g., physical attributes, driver's license, etc.). From these opportunities, the applicant makes a selection. Alternatively, the applicant may elect not to join the Army.

To model this job choice process, we employed discrete choice modeling (McFadden, 1974; Train, 1986). This modeling approach is commonly used in econometrics for modeling the choice behavior of an individual decision-maker, who is assumed to be acting rationally. In constructing the EPAS Simulation JCM, and consistent with other applications of discrete choice modeling, we treat the applicant as the sole decision-maker. It should be noted, however, that we recognize the important role that the guidance counselor plays in the training choices of applicants and integrate it in our model as a factor defining an applicant's choice situation.

There are two major components in the discrete choice modeling framework. The first is the set of alternatives from which the decision-maker chooses. Technically, an applicant at the MEPS is deciding on a training choice that is multidimensional, as characterized by the MOS, reception station date, location, and Term of Service (TOS), and possibly other training reservation variables. Taken together, this involves a very large number of discrete alternatives that is difficult if not impossible to model. Given the specific objective of our analysis, predicting applicants' job choices, we focused mainly on the MOS dimension of the training choice for the purpose of defining the full set of alternatives under consideration, including the option of not joining the Army. Other dimensions in the training choice decision, such as reception station date and TOS, were treated in a secondary manner. Remaining dimensions of training choice were not considered at all. To make the alternative dimensions amenable for model estimation, we further reduced the full set of MOS during the period of interest (FY 2002) from over 150 to 101 by combining comparable MOS with very small reservations, as described later in this report. For any given applicant, typically only a subset of these MOS alternatives will be available in the job list presented to him/her during the course of interacting with the guidance counselor.

The second major component in the discrete choice modeling approach is the rule that governs the decision-maker's choice process. This rule is based on the assumption that the decision-maker behaves rationally. In our problem, we assume that underlying an applicant's training choice are utilities that s/he associates with different MOS training opportunities. Each utility is a score that quantifies the value of an MOS alternative to an applicant. While not meaningful in absolute value, utility is useful for studying the relative attractiveness of MOS alternatives to the applicant. In acting rationally, the applicant is expected to choose the training

alternative with the highest utility. Note that this decision rule is deterministic given the applicant's full knowledge of utilities.[2]

Technically, the utilities used by the applicant to evaluate alternative MOS training opportunities are unobservable to the analyst. To account for this uncertainty, utility is represented as a random variable in discrete choice analysis. We will use U_{ij} to denote the utility that the *i*th applicant attaches to the *j*th MOS alternative (index *j* is relative to the full choice set of MOS opportunities). While the exact value of U_{ij} is known only to the ith applicant, it is reasonable to expect this value to be related to the attributes of the *j*th MOS alternative, such as enlistment incentives and bonuses. Moreover, this value is also likely to depend on the characteristics of the applicant. This incomplete information on the applicant's utility is reflected by writing $U_{ij} = V_{ij} + E_{ij}$, where V_{ij} is deterministic utility reflecting partial information and E_{ij} is a random variable reflecting uncertainty. In the next section, we will fully specify the deterministic utility using known attributes of the MOS alternative, the applicant, and the guidance counselor.

Using the random utility U_{ij} we can mathematically present the general form of a model of applicant choice behavior. Suppose that the *i*th applicant is presented with *m* MOS training alternatives identified by indices 1, 2, ..., *m* ($m < 101$). Since we do not have complete information on the applicant's utility, we can only give a probabilistic statement to identify the MOS alternative that s/he will choose. Specifically, the probability that the applicant chooses the *k*th alternative is given by:

$$\begin{aligned} P_i(k) &= P\left(U_{ik} = \max\{U_{ij} \mid j = 1,2,\ldots,m\}\right) \\ &= P\left(U_{ik} > U_{ij} \mid j = 1,2,\ldots,k-1,k+1,\ldots,m\right) \\ &= P\left(V_{ik} - V_{ij} > E_{ij} - E_{ik} \mid j = 1,2,\ldots,k-1,k+1,\ldots,m\right) \end{aligned}$$

These probability statements reflect our uncertainty (as analysts) regarding the training choice of the applicant because of less than full knowledge about the applicant's utilities, but they do not alter the deterministic nature of the applicant's decision rule. The first line above restates the assumption (or decision rule) that, when making a training choice, applicants seek to maximize utility. Therefore, to completely define the choice model, we need to fully specify the

[2] The assumption of rationality should be addressed in light of the substantial body of research indicating the limits of human rationality in determining choices (e.g., Simon, 1955), the heuristics that are used to evaluate and select decision options (e.g., Kahneman, Slovic, & Tversky, 1982), and the prominence of theories that relax assumptions of rationality (e.g., Kahneman & Tversky, 1979; Klein, Orasanu, Calderwood, & Zsambok, 1993). Knowledge of these limits would suggest ways that individual choices should differ from the assumptions of the discrete choice analysis methodology, in which choice probabilities are used to estimate utility differences. For example, we would expect utility differences for opportunities that are similar in many dimensions (e.g., similar bonuses and/or MOS in the same job family) to be more salient than comparably sized differences between opportunities that differ in nearly all dimensions leading to more extreme choice probabilities for the similar opportunities. Such deviations of choices from the assumptions of the analysis will add some error to the model estimates. Model utility estimates will aggregate choices in a wide range of opportunity combinations, and consequently provide an overall average value that characterizes the cohort. Thus, we anticipate that the modeling framework will be relatively robust to deviations of applicant choices from rationality assumptions.

form of the deterministic component and distributional assumptions on the random component utility. Having done so, we can expect, as stated in the last expression, that as the unexplained utilities E_{ij} s become smaller relative to the explained utilities V_{ij} s, the closer will be the correspondence between applicants' predicted training choices and their actual (observed) training choices (i.e., probabilities for the chosen MOS alternative will be close to 100 percent).

In sum, the main goal of the JCM is to represent the applicant's decision rule as a probabilistic choice model. The response variable in this modeling problem is the choice of an applicant among several alternative MOS, while the explanatory variables are attributes of the MOS training opportunities, characteristics of the applicant, and counselor performance. The model "predicts" choice of MOS in the form of probabilities attached to each alternative MOS in the job list, reflecting the relative likelihood of each being chosen by the applicant. Given its intended application in the EPAS Field Test simulation, to predict applicant job choice, we primarily focus on these probabilities and not on the underlying utilities. Focusing on the utilities would be relevant if the objective of the analysis was to inform incentive policies.

Modeling Applicant Utility

As discussed in the preceding section, and as is common with most prediction problems, precise information regarding variables and their contribution to the unknown utility of a specific applicant for a given MOS is impossible to obtain with absolute certainty. Most important, these variables and their contribution to utilities can (and will) differ from one applicant to another. While we can pool applicants to obtain an "average" utility that applicants who share some characteristic "Z" attach to an MOS alternative with an attribute "X", there remains a residual utility that is not explained by this average. This idea is analogous to traditional regression analysis and is a motivation in partitioning utility into deterministic (or systematic) and random utility, $U_{ij} = V_{ij} + E_{ij}$, where V_{ij} represents average utility and E_{ij} denotes residual utility, which could be due to unobserved MOS attributes and/or applicant "taste" variations.

As a first step in constructing the JCM, we needed to model applicant utilities. This required the following: first, fully specifying the deterministic utility function and its individual components, those variables representing applicant characteristics and choice attributes expected to explain applicants' training choices; and second, specifying the distributional assumptions underlying the residual (or error) utility term. In the following sections we describe how we specified each of these components and operationalized their constituent parts within the EPAS Simulation JCM.

Specifying the Deterministic Utility Function

We specified the deterministic utility function as a linear deterministic utility V_{ij} using a combination of transaction variables that are expected to reasonably represent "average" applicant utility and, therefore, choice behavior. These variables include monetary incentives offered with the MOS, demographics and aptitude scores of applicants, rank order of the alternatives in the applicant job list, and a measure of counselor performance. The last two variables are essential in integrating the EPAS optimization in the JCM.

Let the MOS alternatives be denoted by $j = 1,2,\ldots,101$ and the non-accession alternative by $j = 999$. We partitioned deterministic utility into two main components and an alternative-specific constant by writing V_{ij} as

$$V_{ij}(Z,X,C) = \begin{cases} A_j + V_{ij}(Z) + V_{ij}(X,C) & j = 1,2,\ldots,101 \\ A_{999} + V_{i999}(Z) & j = 999 \end{cases}$$

where

$$V_{ij}(X,C) = B_{Rnk,C_i} X_{Rnk,j} + B_{lsTEA} X_{lsTEA,j} + B_{SBd} X_{SBd,j} + B_{ABd} X_{ABd,j} + B_{HGd} X_{HGd,j} + B_{AA} X_{AA,j}$$

$$V_{ij}(Z) = G_{sexM,j} Z_{Sex,i} + G_{edNG,j} Z_{edNG,i} + G_{edS,j} Z_{edS,i} + G_{edGC,j} Z_{edGC,i} + G_{AQA,j} Z_{AQA,i} + G_{Afqt,NA} Z_{Afqt} + G_{RS,j} Z_{RS,i}$$

The first component, $V_{ij}(X,C)$, is deterministic utility that depends on the attributes X of the MOS alternative (e.g., monetary incentives) and a measure of counselor performance. The counselor performance measure (C) is incorporated into the coefficient B_{Rnk,C_i}, as described below. Note that this component was dropped from the utility function for non-accessions as it describes attributes that are only meaningful to MOS alternatives. The second component, $V_{ij}(Z)$, is deterministic utility that depends on the characteristics Z of the applicant (e.g., gender). The full set of MOS alternative-specific attributes and applicant characteristics used in these equations are summarized in Table 1 (below).

Table 1. List of Alternative-Specific and Applicant Attributes Included in JCM

Variable	Description
Alternative-Specific Attributes:	
$X_{Rnk,j}$	Relative rank of the *j*th MOS alternative in the job list.
$X_{lsTEA,j}$	Expected maximum utility of applicant for the EB/ACF/LRP incentive package available for the *j*th MOS. The form of this composite utility is given below.
$X_{SBd,j}$	Seasonal bonus dollars offered with the *j*th MOS alternative (in thousands).
$X_{ABd,j}$	Airborne bonus dollars offered with the *j*th MOS alternative (in thousands).
$X_{HGd,j}$	High-Grad bonus dollars offered with the *j*th MOS alternative (in thousands).
$X_{AA,j}$	Aptitude area score of the applicant for the *j*th MOS alternative.
Applicant and Counselor Characteristics:	
$Z_{sexM,i}$	Sex indicator variable for male (1=Male, 0=Female)
$Z_{edNG,i}$	Indicator variable for non-graduate education status

$Z_{edS,i}$	Indicator variable for senior education status
$Z_{edGC,i}$	Indicator variable for education status beyond high school graduate (i.e., at least some college semester hours)
$Z_{AQA,i}$	Indicator variable for AFQT Category I-IIIA
$Z_{RS,i}$	Indicator variable for South Region geographic location
Z_{Afqt}	AFQT percentile score
C_i	Measure of counselor performance based on the 60th percentile of the ranks of MOS reservations processed

In the equations above, the B- and G-weights describe the relative importance of associated MOS alternative attribute or applicant characteristics to the total utility. These weights and alternative constant A_j are parameters to be estimated from the transaction data. Greater detail on the variables representing the alternative attributes and applicant characteristics and how they were specified in the JCM are summarized in the following sections.

Rank Order Effect. In general, MOS alternatives that are important to Army enlistment goals appear at the top of applicants' opportunity (or job) lists. Operationally, this can be represented by the variable $X_{Rnk,j}$, where the rank order of an MOS alternative (within a job list) is expressed as a percentage relative to the total number of opportunities in the list. However, unlike the monetary incentives, this attribute (by itself) is not expected to directly contribute to applicants' utility. That is, an applicant is not expected to be "attracted" to an MOS just because of its rank order in the list. Instead, the extent to which an applicant selects an MOS at the top of the job list, excluding the effects of monetary incentives, will depend on the guidance counselor's ability to "sell" these jobs. A higher ability counselor should be able to sell higher-ranked MOS compared to a lower ability counselor, when facing applicants with similar (observed and unobserved) characteristics and job lists with comparable MOS and monetary benefits.

Consistent with this, we expanded the operationalization of the effect of rank of an MOS on applicant utility to include counselor ability. To do this, we computed an empirical measure C_i to index the ability of the counselor that the *i*th applicant faced at the MEPS. This performance measure was based on the 60th percentile of the overall ranks of MOS in reservations made by all applicants processed by the counselor during the period covered by the estimation sample.[3] The weight (or effect) of rank order attribute $X_{Rnk,j}$ for the ith applicant was then reformulated as $B_{Rnk,C_i} = B_{Rnk} + B_C C_i$. The utility term corresponding to rank order then becomes

[3] The *overall* rank used to compute the measure C_i uses the rank order of an MOS relative to all MOS that were available on a given transaction date, and not the rank order relative to the job list of an applicant. The overall ranking of MOS was "estimated" using rank ordering information from job lists of applicants during a given transaction date.

$$\begin{aligned} B_{Rnk,C_i} X_{Rnk,j} &= (B_{Rnk} + B_C C_i) X_{Rnk,j} \\ &= B_{Rnk} X_{Rnk,j} + B_C \left(C_i X_{Rnk,j} \right) \end{aligned} \quad (1)$$

From the second line expression, the rank order term of utility may also be viewed as a main effect plus an interaction between MOS rank order in the job list and counselor performance. It is important to note that in applying the JCM to simulate applicant choices, an assumption is that the Army priority rank ordering and the combined EPAS-Army priority rank ordering are not distinguishable to a counselor.

The contribution of the rank order term above to total utility of the applicant represents "partial effect" as in typical regression analysis. It is "partial" in the sense that it accounts for the applicant's utility not already explained by monetary incentives and other factors included in the utility function. This note is important since monetary incentives and rank order are highly correlated by design. A utility model that fails to properly account for monetary benefits will overestimate the role of the guidance counselor in applicant selection of "high ranking" MOS alternatives (and vice versa). That is, it will confound counselor ability with the effects of monetary incentives and, therefore, lead to biased EPAS Field Test results.

Monetary Incentives. The attributes $X_{lsTEA,j}$, $X_{SBd,j}$, $X_{ABd,j}$, and $X_{HGd,j}$ represent Army incentive policy. The first attribute is a composite of Enlistment Bonus (EB) and Army College Fund (ACF) incentives, which are tied to the TOS. Also included in this attribute is the Loan Repayment Program (LRP) package, which is offered in place of ACF. The form of this composite is described in more detail below. The other three attributes represent distinct monetary incentives. As with EB/ACF, the dollar values in these incentives differ across MOS, reflecting MOS importance to the Army's enlistment goals. The availability and dollar amount of incentives can also differ depending on the applicant's qualifications for a given MOS. For instance, the overall value of the EB/ACF incentive package is highest for 11X, reflecting the importance of the MOS to the Army's mission. This incentive package is only available to AFQT I-IIIA applicants. The purpose of the Seasonal Bonus (SB) incentive is to encourage enlistment into and fill of near term training classes. It is given in three levels depending on how close the start date of a training opportunity is at the time of the transaction. For a given SB incentive level, different dollar amounts are offered to AFQT I-IIIA and IIIB applicants. Similarly, Hi-Grad (HG) incentive dollars are available to applicants with some college education if they enlist in "incentivized MOS" (i.e., MOS eligible for EB/ACF incentives). The HG dollar amount also differs depending on whether the applicant has earned at least 30 or 60 college semester hours. Overall the net effect of these incentives is to make certain MOS more attractive than others to particular types of applicants.

As mentioned above, the variable $X_{lsTEA,j}$ was computed as a composite of cash bonus and ACF dollars computed from the EB, EB+ACF combo, and ACF incentive packages available to an AFQT I-IIIA applicant signing up for about 80 to 90 MOS. By design, the Army has constructed its incentive policy such that the availability of these three types of EB/ACF incentives and the associated dollar amounts depends on the MOS and TOS. For high priority MOS, these incentives (EB and EB+ACF) are available in higher dollar amounts even for short TOS (2 or 3 years). For middle priority MOS, EB and EB+ACF incentives are offered but with

smaller dollar values and only starting with at least 4 years TOS. For lower priority MOS, bonus dollars (either from EB or EB+ACF) in relatively small amounts may be available but only for longer TOS (5 or 6 years), and in some cases only ACF is available.

We treated the EB/ACF component of utility differently from the others for several reasons. First, as described above, different types of EB/ACF incentive packages are available for the same MOS. This situation differs from the other incentives whose dollar value (and form) stays the same for a given MOS. Second, unlike the other incentives that are independent of TOS, the applicant's choice from the EB/ACF incentive package cannot be separated from TOS--a dimension of applicant's training choice that is not important to the current problem. Third, Army incentive policy tends to treat EB and ACF incentives interchangeably, frequently combining the two into a single package, such that the incentives represent dependent rather than independent effects. For these reasons, we elected to integrate the EB/ACF incentives into a single variable in the JCM.

To do this, we formed a composite to represent applicants' expected utility from the many EB/ACF incentives and TOS possibilities for a given MOS. We also included the LRP incentive in this composite, as it is offered in place of ACF for some applicants. Separate composites were formed for AFQT I-IIIA and IIIB applicants since the latter are not eligible for EB/ACF incentives. The most general form of this composite is given by

$$X_{IsTEA,j} = \log \sum_t \exp\left\{ \frac{1}{M_t} \log\left[\exp\left(M_t V_t^*\right) + \exp\left(M_t V_{E,t}^*\right) + \exp\left(M_t V_{A,t}^*\right) + \exp\left(M_t V_{EA,t}^*\right)\right]\right\}$$

where M_t is a positive constant that depends on TOS for the incentive. The terms in the inner log expression correspond to the different types of EB/ACF incentive, respectively: (1) none, (2) EB-only, (3) ACF-only, (4) EB+ACF combo; summation is over number of years (t) of TOS. For a specified MOS, only terms corresponding to EB/ACF incentives that were available to the applicant are included inside the curly-braces.

Taken as a whole, the composite $X_{IsTEA,j}$ aims to capture the applicant's expected utility for alternative EB/ACF incentives and TOS for the *j*th MOS alternative. The *V* quantities in the composite represent utilities associated to the four types of EB/ACF incentives, and are given by:

$$\begin{aligned} V_t^* &= A_t + B_L I_L \\ V_{E,t}^* &= A_t + B_E X_{E_1,t} + B_L I_L \\ V_{A,t}^* &= A_t + B_A X_{A_1,t} + B_S\left(I_S X_{A_1,t}\right) \\ V_{EA,t}^* &= A_t + B_E X_{E_2,t} + B_A X_{A_2,t} + B_S\left(I_S X_{A_2,t}\right) \end{aligned}$$

where

$X_{E_1,t}$ = bonus dollar value of EB incentive for a TOS of *t* years;

$X_{E_2,t}$ = bonus dollar value of EB+ACF incentive for a TOS of *t* years;

$X_{A_1,t}$ = ACF dollar value of ACF incentive for a TOS of t years;
$X_{A_2,t}$ = ACF dollar value of EB+ACF incentive for a TOS of t years;
I_L = indicator variable representing the availability of the LRP incentive for the MOS;
I_S = indicator variable for senior education status.

The LRP incentive was represented in the composite using an indicator variable since only maximum loan is specified. It only appeared in the first two types of incentives, as it cannot be combined with ACF. The ACF dollar value used in the composite is less than the Montgomery GI Bill amount of $23,400 dollars.[4] The contribution of ACF to utility includes an interaction involving high school senior education status of the applicant. We included this interaction because seniors can be expected to find ACF incentives more attractive than non-high school graduates and/or high school graduates with some college. The quantities A and B are parameters to be estimated from the transaction data.

Aptitude Area. The variable represented by $X_{AA,j}$ is the aptitude area (AA) score of the applicant corresponding to the jth MOS alternative. It is the only alternative-specific variable that does not represent Army priority. The value of $X_{AA,j}$ is a measure of the applicant's aptitude for the type of job that characterizes the jth MOS (e.g., Clerical, Mechanical, etc.). AA scores play important but meaningfully different roles in REQUEST and EPAS. The REQUEST system uses the AA score as a key variable in determining the eligibility of an applicant (e.g. only MOS whose minimum enlistment standards are met by an applicant will appear in his/her job list). The EPAS model employs the AA score in its person-job-match optimization, which aims to identify the MOS best suited for the applicant subject to Army enlistment priority constraints. Because the value of this variable is believed to generally reflect the vocational interests of the applicant, it is expected to contribute to their utilities for MOS alternatives.

Applicant Characteristics. As the Army intends, the monetary incentives discussed above are expected to make some MOS more attractive than others. However, their overall effect on training choices is not likely to be uniform across applicants. For example, the relatively high EB dollars available to priority MOS (for signing up for a TOS of six years) may not be appealing to a high school senior who plans to go to college. Likewise, mechanical jobs are likely to be more attractive to male than female applicants. Because of these differential effects on training choices, we added applicant characteristics to the utility function of applicants.

The specific applicant characteristics included in the utility are: (1) gender; (2) education status; (3) AFQT; and (4) applicants' geographic location. These characteristics were selected for two reasons. First, these are known to impact the type of MOS preferred by applicants. Second and more importantly, most of these characteristics are relevant to EPAS in that they define the supply groups, which represent applicants in the EPAS optimization algorithm. By including these characteristics in the JCM, one can obtain, for example, percentages of applicants

[4] The EB/ACF/TOS composite was motivated by an expanded model with choice dimension (MOS, TOS, EB/AC incentive). The A and B parameters were estimated from the transaction data using applicants choice of MOS, TOS, and EB/ACF incentive.

in a supply group that will prefer alternative MOS, which itself could be directly useful in the EPAS optimization routine.

To incorporate applicant characteristics into the JCM, indicator variables were created to represent group membership, except for AFQT percentile score (Z_{Afqt}), which was treated as a continuous variable and whose values reflected applicants' AFQT percentile scores. Gender, represented in the utility by $Z_{sexM,i}$, constituted the indicator variable for male applicants. To further capture meaningful differences in education status, the three categories used in defining education status for the EPAS supply groups were expanded to four. In addition to non-graduates ($Z_{edNG,i}$) and seniors ($Z_{edS,i}$), the high school graduate status was divided into two separate categories: (1) one for those who earned a high school diploma but did not attend college; (2) and one for those who attended college. The latter is represented by the indicator variable $Z_{edC,i}$. AFQT category is represented in the utility using the indicator variable $Z_{AQA,i}$ for AFQT I-IIIA applicants. We included the AFQT I-IIIA indicator variable, in addition to the percentile score, because separating applicants who are eligible from those who are not eligible for incentives provides meaningful information, as most incentives require an applicant to be in the AFQT I-IIIA category range.

Since for any given applicant these characteristics are *fixed* across the alternative MOS within his/her job list, their differential effect can only be achieved in our modeling approach by using MOS alternative-specific weights in the utility. However, given the large number of MOS alternatives, varying parameters for each MOS is computationally prohibitive. Additionally, a number of these parameters are not likely to vary substantially since many MOS share common characteristics. For these reasons, we only used 10 weights for each applicant characteristic; nine weights specific to the aptitude areas for alternatives representing Army MOS, plus another weight for the alternative representing non-accession. An exception was AFQT percentile score, for which we only specified a non-zero weight for the non-accession alternative.

Specifying the Random Utility Distributional Assumptions

In addition to specifying the deterministic utility function, we needed to specify the distributional assumptions about the random errors E_{ij} s in applicant utilities, which in full are given by

$$U_{ij} = \begin{cases} A_j + V_{ij}(Z) + V_{ij}(X,C) + E_{ij}, & j = 1,2,\ldots,101; \\ A_{999} + V_{i999}(Z) + E_{i999}, & j = 999. \end{cases} \tag{2}$$

Doing so would fully describe the structure of the applicant's utilities. As in most analyses, we assumed that training choice observations, and by implication the E_{ij} s, across applicants are statistically independent. For the intra-individual correlation structure, the E_{ij} s are usually

assumed to be independent and identically distributed as a Type I extreme value distribution.[5] However, the latter assumption raises two implications that are difficult to justify. We describe the issues below and provide an alternative error structure specification.

First, the assumption states that the variance of E_{ij}, which represents our uncertainty, is the same for both MOS and non-accession alternatives. This assumption was difficult to justify. For one, the extent of our knowledge of the applicant's utility is different for non-accessions compared to MOS alternatives, as indicated by the difference in their systematic components shown in the equation above. Equally as important, we were dealing with two different types of alternatives, specifically, military jobs and civilian jobs. Therefore, to account for potential differences in error variance of random utility, we specified a common scale for MOS alternatives and a different scale for the non-accession alternative.[6]

Second, the usual distributional assumption regarding E_{ij} also implies that the error variance of utility is the same across individual recruits for a given alternative (i.e., errors are homoscedastic). This is separate from the first issue above, which compares error variance between alternative utilities. It is of special concern in relation to the more than 20 percent of total applicants with job "lists" consisting of a single MOS opportunity, since EPAS is not expected to achieve direct classification efficiency from these individuals. Failing to address potential heterogeneity in error variance of single- and multiple-opportunity applicants' utility could lead to over- or under-estimation in the remaining 80 percent of the applicant population. To account for this heterogeneity we included a scale factor for single-opportunity applicants, thereby yielding a different error variance compared to that of multiple-opportunity applicants.[7]

In sum, the following are the final distributional assumptions for the random variable E_{ij} adopted for our JCM after adding the two error variance modifications. These assumptions completed the mathematical structure of the applicant's utility.

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[5] The Type I extreme value distribution with scale parameter σ has cumulative distribution function $F(\varepsilon) = \exp\{-\exp[-\sigma\varepsilon]\}$. This distribution has a mean of zero and variance $\pi^2/(6\sigma^2)$. Note that the scale parameter is inversely proportional to the error variance.

[6] The scale parameter for MOS alternatives was specified *a priori* to be greater than or equal to that for non-accession. While this relationship was more of a constraint in our modeling approach, it can be justified for two reasons. First, the systematic utility for MOS alternatives includes more observed information than that for non-accession. Second, the utility for non-accession alternative represents diverse civilian jobs while that for MOS alternatives represent specific military jobs. These two observations will have the effect of making the error variance of random utility for MOS alternatives lower compared to that for the non-accession alternative, or, equivalently, making the MOS scale parameter greater than that for the non-accession alternative.

[7] Two types of individual who are likely involved in single-opportunity transactions are: (1) applicants who are eligible for one or two MOS only; and (2) applicants who seek specific MOS, often regardless of monetary incentives. An inspection of the data appears to support these two cases. Out of the top five MOS involved in single-opportunities, three have relatively low minimum-standards, specifically: 11X (Infantry), 92G (Food Service Operations), and 88M (Motor Transport Operator). The other two MOS are 95B (Military Police) and 91W (Health Care Specialist), which respectively have moderate to high minimum-standards and appear to be sought after despite having very low monetary incentives. The first two MOS involved applicants whose training choices reflect decisions made with limited options. The other three MOS involved applicants whose training choice decisions are based heavily on specific factors. The utilities of applicants in both cases possibly are not represented as well by the systematic utility V_{ij}, thereby yielding relatively larger error variance.

(1) The E_{ij} s are independent across individual applicants.

(2) The distribution of E_{ij} 's is Type I extreme value with variance that is characterized by the positive constants δ and λ as follows. The variance of the non-accession alternative is λ^2 times that of an MOS alternative, and the variance for applicants with multiple opportunities is δ^2 times that for applicants with a single opportunity.

(3) For the *i*th applicant with multiple opportunities, the variance of E_{ij} 's is $(\delta\pi)^2/(6\lambda^2)$ for MOS alternatives (j=1,2,...,101) and $(\delta\pi)^2/6$ for the non-accession alternative (j=999).

(4) For the *i*th applicant with a single opportunity, the variance of E_{ij} 's is $\pi^2/(6\lambda^2)$ for MOS alternatives (j=1,2,...,101) and $\pi^2/6$ for the non-accession alternative (j=999).

(5) Random errors associated with MOS alternatives $(E_{i1}, E_{i2}, \ldots, E_{i101})$ are independent of the random error for the non-accession alternative (E_{i999}).

(6) Conditional on the *i*th applicant joining the Army, the random errors $(E_{i1},, \ldots, E_{i101})$ are independent.

Probabilistic Job Choice Model

Having specified the deterministic utility function and the distributional assumptions of the residual utility term, we now specify the full form of the applicant's probability choice model separately for multiple- and single-opportunity applicants. To keep our expressions compact, we employ the following substitutions in our model formulas:

$$V_{ij}(Z_i, X_{ij}, C_i) = A_j + V_{ij}(Z) + V_{ij}(X, C)$$
$$V_{i999}(Z_i) = A_{999} + V_{i999}(Z)$$

Multiple-Opportunity Applicant. Given that applicants are expected to behave rationally and that their utilities are given by equation (2) with the aforementioned distributional assumptions, then the training choices of applicants can be described by the Nested Logit (NL) probability model, with MOS alternatives forming one nest and the non-accession alternative constituting a nest of its own. Mathematically, this can be represented as follows.

Without loss of generality, suppose that the job list of the *i*th applicant is comprised of the MOS alternatives labeled $j = 1,2,\ldots,m$, then the probability that s/he chooses the *k*th MOS alternative can be given by

$$P_i(k)=\frac{\exp[\delta\lambda V_{ik}(Z_i,X_{ik},C_i)]\times\left\{\sum_{j=1}^{m}\exp[\delta\lambda V_{ij}(Z_i,X_{ij},C_i)]\right\}^{\frac{1}{\lambda}-1}}{\exp[\delta V_{i999}(Z_i)]+\left\{\sum_{j=1}^{m}\exp[\delta\lambda V_{ij}(Z_i,X_{ij},C_i)]\right\}^{\frac{1}{\lambda}}},\ k=1,2,\ldots,m$$

while the probability that s/he chooses not to join the Army can be given by

$$P_i(999)=\frac{\exp[\delta V_{i999}(Z_i)]}{\exp[\delta V_{i999}(Z_i)]+\left\{\sum_{j=1}^{m}\exp[\delta\lambda V_{ij}(Z_i,X_{ij},C_i)]\right\}^{\frac{1}{\lambda}}}.$$

The NL model form describes or "estimates" training choice by providing a probability that the *i*th applicant with characteristics Z_i, who is being processed by a guidance counselor with performance measure C_i: (1) chooses the *k*th MOS alternative among *m* alternatives with attributes $(X_{i1}, X_{i2}, \ldots, X_{im})$; or (2) decides not to join the Army. This probability has an "average" interpretation from the researcher's point of view. That is, over many samples of applicants with the same characteristics and the same alternatives and attributes, the probability represents the proportions of applicants with specified characteristics who chose a given alternative.

Alternatively, the model can also be expressed in *sequential probability* form, which describes an applicant's decisions using two "levels": (1) to join (or not join) the Army; and (2) MOS choice if joining the Army. It can be verified algebraically that for alternatives $k=1,2,\ldots,m$ the choice probability is

$$P_i(k)=[1-P_i(999)]\times P_i(k\mid\text{join Army}).$$

where

$$P_i(k\mid\text{join Army})=\frac{\exp[\delta\lambda V_{ik}(Z_i,X_{ik},C_i)]}{\sum_{j=1}^{m}\exp[\delta\lambda V_{ij}(Z_i,X_{ij},C_i)]}.$$

The factor $[1-P_i(999)]$ is just the probability that the applicant will join Army. The factor $P_i(k\mid\text{join Army})$ is the probability that he will choose the *k*th MOS alternative among *m* alternatives conditional on his/her joining the Army. The form of $P_i(k\mid\text{join Army})$ is also known as the Multinomial Logit (MNL) model.

Single-Opportunity Applicant. The probability choice model for single-opportunity applicants is different in form but consistent with the above models for multiple-opportunity applicants. For the *i*th applicant with only one option represented by the *k*th MOS alternative, the probability for choosing the *k*th MOS over non-accession is given by

$$P_i(k) = \frac{\exp[V_{ik}(Z_i, X_{ik}, C_i)]}{\exp[V_{i999}(Z_i)] + \exp[V_{ik}(Z_i, X_{ik}, C_i)]}$$

The probability for not joining the Army is simply $P_i(999) = 1 - P_i(k)$. This simpler form is just the logistic probability model.

Taken together, the different probability functions above represent the major components of a single, probabilistic JCM. The constants, weights, and scale parameters for the accession/non-accession and MOS choice components of the model combine to characterize the JCM and must be jointly estimated. Because of the large number of model parameters, we employed a two-stage estimation strategy by taking advantage of the two-level sequential probability form of the model. The first stage involved estimating the parameters in the conditional MNL model $P_i(k \mid \text{join Army})$ using an iterative process (detailed in the next part of the report). Only multiple-opportunity applicants were used in this stage. In the second stage, we estimated all parameters in the combined two-level model, including those associated with the decision to join or not join the Army, using both single- and multiple-opportunity applicants. Parameter estimates obtained in the first stage were used as starting values in the second stage.

ESTIMATING AND EVALUATING THE JOB CHOICE MODEL (JCM)

Having constructed the JCM, we moved to estimate its major components for use in the EPAS Simulation. In the following sections, we detail our procedure for estimating these components. Most important, we document and discuss the results of an empirical evaluation of the model's accuracy for simulating applicants' actual job choices.

Estimation Samples

All JCM estimates were based on Army applicant and accession data covering Fiscal Year (FY) 2002. For modeling and estimation purposes, we partitioned the FY 2002 into four quarters based on the effective dates of the EB/ACF incentive packages produced by the Army's quarterly Enlistment Incentive Review Board (EIRB) meetings.[8] Separate models were estimated by EIRB quarter, using the cut-off dates and sample sizes shown in the table below. Note that calendar and EIRB quarters closely match but do not coincide. In particular, the first quarter starts later than the actual effective date of 11 September 2001, while the last quarter continues for one more week past the EIRB end-date of 23 September 2002.

[8] The EIRB is comprised of policy representatives from G-1, USAREC, and HRC. They review the existing incentive structure vis-à-vis MOS fill to-date and training seat availability, and may recommend incentive changes aimed toward making MOS targets at least cost.

Table 2. JCM Estimation Quarters and Sample Sizes

Quarter	Start Date	End Date	Total Size	Sample Size
1	October 1, 2001	December 3, 2001	14,236	4,085
2	December 4, 2001	March 3, 2002	22,049	4,390
3	March 4, 2002	June 2, 2002	24,264	4,395
4	June 3, 2002	September 30, 2002	32,407	4,421

A few alternatives were relatively large compared to the others. For example, 11X and non-accessions accounted for over 30% of all applicants, while fewer than 10 out of a total of 102 MOS alternatives accounted for more than 50% of all applicants. Because of the potential for under (and over) representation, we employed a choice-based sampling strategy to ensure that all MOS alternatives were adequately represented in the estimation sample. To carry out this sampling strategy, we first grouped applicants according to their chosen MOS (or non-accession). Applicants were then selected by under-sampling from the larger MOS groups and over-sampling from the smaller MOS groups. To ensure that our sampling strategy did not artificially bias JCM estimates, we assigned weights to applicants during model estimation that were equal to the reciprocal of the sampling rates in their respective MOS groups.

Data Preparation and Simplification

Information on applicants' attributes and job opportunities represent real-world data. Because of this, and as is characteristic of most non-experimental data, certain features of the data were not directly amenable to our modeling approach without simplification and/or restructuring. For example, some applicants had more than one search date, indicating that they had visited the MEPS multiple times before making a final decision or at some point changed their mind. While having multiple search dates reflects a legitimate, real-world property of the data, such a feature does not lend itself to a straightforward and parsimonious application of our approach without greatly increasing (unnecessarily) the complexity of the JCM. Therefore, to minimize potential problems with the data, we made several simplifications and modifications to the data prior to estimating the JCM. In all cases, our goals in preparing and simplifying the data were twofold: first, to retain meaningful real-world features of the data to ensure the realism and generalizability of the EPAS Simulation, and most importantly, its results; and second, to increase the reliability of the data to ensure that it met basic model requirements so as to produce a meaningful (and accurate) evaluation of the JCM.

Specifically, there were four major features of the data requiring attention. These were: (1) identifying applicants' search dates for use in the JCM estimation and EPAS simulation, as a number of applicants had multiple search dates; (2) including or excluding applicants with job opportunity lists consisting of a single opportunity, as these applicants' choice behavior (and preferences) were likely different from those of most applicants; (3) aggregating applicants' job opportunity lists, as a sizeable percentage of applicants made multiple queries (within the same

search date); and (4) configuring the job choice space. In the following subsections, we briefly summarize each issue and how each was handled and why.

Identifying Applicants' Search Dates for JCM Estimation and EPAS Simulation

Inspection of the data indicated that there were a number of applicants with multiple search dates. Consequently, we were faced with the issue of how to handle applicants with multiple search dates. While this usually represented a legitimate feature of the data (and not a data entry error), as there are applicants who make multiple visits to the MEPs before making a final job choice decision, the inclusion of multiple search dates into the JCM would have greatly added to the complexity of the model. To simplify the model, we elected to use the search date matching the applicants' reservation date. There were two reasons for this: first, because the search date from which the actual job choice was made represents the choice space most proximal to an applicant's actual decision, it should exert the greatest influence on their job choice; and second, including the most recent search date already captures the "effects" of previous search dates. That is, it is reasonable to expect that opportunities presented on the final search date are largely a function of applicants' preferences and choice behavior manifested during earlier search dates. Therefore, including past search date information is not likely to add appreciably to the JCM estimation, since its "effects" are transmitted through the most recent search date.

Applicants with Single Opportunity Job Lists

One issue that we faced at the beginning was how to deal with applicants with a single job opportunity, whether to exclude or include them in model estimation. A substantial percentage of applicants (roughly 20%) had job opportunity lists consisting of a single opportunity. There are two reasonable explanations for this: (1) that these applicants came to the MEPS with well-defined preferences and were interested in a specific job (MOS); or (2) that these applicants were eligible for a limited number of MOS only (e.g., female applicants with low AFQT scores). These applicants contribute to the first-level of the JCM (i.e., join or not to join the Army) but not directly in the second-level as their MOS is "fixed" once they decide to join the Army. We included these applicants in our model but treated them differently from applicants with multiple-opportunities. (Technical details were provided earlier in our mathematical description of the JCM.) There were two reasons for this. First, because the preferences and choice behavior of applicants with single job opportunities likely differ from that of most applicants. For instance, whereas most applicants' decisions to access or not access will partly be a function of the relative attributes of the available job opportunities, these applicants' decisions are likely determined mainly by the simple (un)availability of the preferred opportunity. Second, while these single opportunity applicants are beyond the reach of EPAS optimization, they contribute to the entire Army accession cohort and therefore impact the EPAS model. The "first case" applicants clearly hold strong and well-defined preferences, and EPAS is not likely to exert much of an influence on their job choice decisions. In sum, these applicants are part of real-world REQUEST and excluding them or "fixing" their choices biases the model and field test evaluation.

Aggregating Applicants' Job Opportunity Lists

Many applicants made multiple queries within the same search date. This raised the question of how to deal with multiple queries, which produced multiple opportunity lists whose similarity in MOS-reception dates varied. Comparable to multiple search dates, while this

feature represents a legitimate facet of the data, its inclusion would have added significant complexity to the model. To simplify this data feature, we elected to aggregate opportunities across queries (within the same search date), dropping duplicate MOS-reception date opportunities and reordering the rank order of opportunities based on the combined list. This approach was taken for several reasons. The first reason is that *all* opportunities presented define the choice space for the applicant. For example, applicants may make a job choice at any time, irrespective of whether the opportunity appears in the current query. While modeling multiple queries unnecessarily increases model complexity, excluding opportunities artificially truncates the choice space and limits a meaningful real-world feature of the data, as it ignores opportunities considered by applicants when making their decisions. This in turn potentially biases JCM probability estimates of applicant choices, which are conditional on the *full* set of alternatives (and not an artificially defined subset). A second reason for the approach selected is that Army counselors, who potentially play a significant role in applicants' job choice decisions, are likely to treat multiple queries as a single query. That is, counselors are normally familiar with the Army's prioritization of job opportunities. Because they are incentivized to do so, counselors can reasonably be expected to "sell" applicants on the highest priority job(s), irrespective of the particular query said job(s) appear in. Therefore, excluding opportunities could further bias JCM estimates (positively or negatively) because it minimizes an important effect, counselor performance, which meaningfully contributes to applicants' choice behavior.

Configuring the Job Choice Space

Inspection of applicants' job (MOS) choices indicated that across the full fiscal year there were upwards of 155 total MOS to select from. While including all possible jobs may be ideal from a conceptual standpoint, practically this represented a considerably large choice space to define computationally and model accurately. To address this, we elected to reduce the choice space by combining jobs (MOS), specifically jobs with small sample sizes (n), that were: (a) similar in job content (i.e., were members of the same Career Management Field or Aptitude Area); and (b) similar in their incentive profiles. There were several reasons recommending this approach. First, reducing the choice space would minimize potential estimation problems resulting from the increased dimensionality (and complexity) of the original choice space. Second, increasing the n of these jobs increases the accuracy of the model estimates. Both minimize the possible bias in JCM estimates without sacrificing important information, as the jobs combined represent jobs with similar attributes and therefore are likely to elicit similar preferences (utilities) from applicants. When done, the final job choice configuration consisted of 101 MOS alternatives, which across the four FY quarters represented 99%-100% of the original job choice space and resulted in a doubling (on average) of the median n. These MOS alternatives are reported in Table A.1.

Estimation Procedure

Consistent with our design, JCM estimates were generated by FY quarter using the applicable sample. For each quarter, the estimation procedure consisted of the same two-stage process, as follows:

Stage One: Estimating the Second-Level of the JCM. In the first stage, estimates for the JCM were computed for the second-level of the model, applicants' job opportunity choice, using the multinomial logit model (MNL) described in the preceding part of the report. Estimating the MNL followed a multi-step, iterative process. In the first step, a main effects MNL was estimated. This main effects MNL consisted of multiple-opportunity applicants and MOS alternative-specific attributes, and counselor performance, as documented in the preceding part of the report. After estimating this main effects model, we evaluated overall model fit and fit by the different subgroups and job types (or MOS aptitude areas) to ensure that the second-level JCM reasonably predicted applicants' actual choices. In all cases, this evaluation indicated that model fit at the subgroup (i.e., gender, education status, etc.) and job type (i.e., Clerical, Combat, etc.) levels could be significantly improved by adding selected interaction terms to the MNL. The purpose of interaction terms is to capture meaningful differences in MOS preferences by applicant characteristics (e.g., gender differences in preferences for Clerical jobs, such that females tend to prefer these jobs more than male applicants). Using fit diagnostics at the subgroup and job type level as a guide, interaction terms were selectively added to the MNL. This continued until fit diagnostics at the subgroup and job type levels met desirable levels of fit, at which point the model estimation process was stopped. As will be demonstrated in the next section, adding interaction terms produced substantial increments in fit, particularly at the subgroup and job type level.

Stage Two: Estimating the First-Level of the JCM. In the second stage, estimates were additionally computed for the first-level of the JCM, applicants' decision to join (or not join) the Army, using the nested logit model (NL), also summarized previously. The parameters in the first-level JCM were re-estimated in this stage, using estimates obtained in the Stage One as starting values. The parameter estimates obtained in this stage specify the full two-level JCM estimate. The second stage estimation was not carried out until the MNL (at the first stage) demonstrated desirable (and comparable) levels of model fit both overall and across the different subgroups and job types. Because the increased complexity of the NL models increases the computational time and resources required for estimation, estimation proceeded iteratively until: (1) a desirable level of model fit was obtained; and (2) subsequent iterations failed to produce significant increments in model fit, either overall or at the subgroup and job type level. When these criteria were met, NL estimation was halted even if the model had not fully converged.

Details on observed fit for the MNL and NL models (by quarter) and specific criteria used are documented further in the next section. All JCM estimates for both the MNL and NL were computed using the BIOGEME software (Bierlaire, Bolduc, & Godbout, 2003).

Estimation Results and Fit Diagnostics

The JCM parameter estimates obtained at the end of the two-stage estimation procedure are presented in Appendix B. The alternative-specific constants for each MOS are reported Table B.1. The B- and G-weights in the deterministic utility and scale parameter for the random utility are reported in Table B.2. To facilitate comparisons across quarters, rescaled versions of the estimates are reported in Tables 2 and 3 for the first 20 MOS alternatives and non-accession

constants, coefficients for all alternative-specific attributes and selected applicant characteristic.[9] Model fit diagnostics are reported in Appendix C.

Utility Parameter Estimates

As can be seen from Table B.1, across all quarters, most MOS alternative-specific constants are negative, reflecting the fact that, on average, most MOS are associated with lower utilities compared to 11X (Infantry).[10] This makes sense since 11X: (1) is open to virtually all recruits, particularly low-aptitude recruits with fewer job choices; (2) tends to be highly incentivized to attract large number of applicants; and (3) is always a high priority (or highly ranked) MOS. Consequently, the probabilities of applicants joining 11X tend to be higher, on average, than those for other MOS. The only MOS for which this is consistently not the case across all four quarters is 98X (EW/SIGINT Specialist-Linguist). Similarly, these differences between 11X and the other MOS tend to be statistically significant (see "T-stat" column; significant differences, $p < .05$ are bolded). On average, roughly 10% of the other MOS per quarter display baseline utilities comparable to 11X. Alternative-specific constants are also generally comparable across four quarters in terms of their rank ordering.

Turning to Table 4, among alternative-specific attributes, those that consistently exhibited significant effects on applicant choices across quarters are: (1) rank order of the MOS; (2) counselor performance; (3) SB incentive; and (4) AA score. Estimates of rank order coefficient are consistently negative and statistically significant for all quarters. Because alternatives at the top of the job list have lower numeric rank order values, it is important for this parameter to be negative for EPAS to have a positive impact on REQUEST. However, as described by equation (1), the overall weight of rank order is dependent on the performance of the counselor processing the applicant, which has positive significant coefficient across quarters. The combined effect of this interaction is that the potential positive impact of EPAS on REQUEST can be expected from better-performing counselors but not from counselors performing poorly.

Among the monetary incentives, only SB consistently exerted a positive, significant effect on applicants' job choices across all quarters. The positive SB coefficient estimates can be interpreted to mean that the incentive was effective in making near term training class seats attractive to applicants. The interaction between SB incentive and high school senior education status is significantly negative for the third quarter, but not significant for the other three quarters. This is not surprising given that seniors generally would not be able to access near term MOS alternatives during the third quarter, which would be around the last three months of the school year (i.e., March, April, and May). The results for the other monetary incentives are mixed. The TOS+EB+ACF composite utility (see pp. 8-9) has a positive significant effect in the fourth quarter, a not significant (but somewhat substantial) positive effect in the first quarter, and not significant negative effect in the second and third quarters. The AB incentive has positive significant effect in the first quarter, not significant but non-negligible effect in the second and

[9] B- and G-weights are reported "relative" to the scale of the utilities for single-opportunity applicants. To obtain parameters relative to the majority of applicants with multiple opportunities, estimates corresponding to MOS alternatives were multiplied by LAMDA and DELTA estimates while those corresponding to the non-accession alternatives (suffix by 999) were multiplied by DELTA.

[10] Readers are reminded not to interpret the absolute level of the constants to mean that the utilities for most MOS are negative, as these values are not average applicant utilities. These constants reflect the standing of an MOS *relative* to 11X and therefore represent differences in (average) utility between an MOS and 11X.

third quarter, and not significant negative effect in the fourth quarter. The HG incentive has a substantial but not significant negative effect in the last three quarters. This appears not surprising given that an intended policy goal of the incentive, to make the Army attractive to college individuals, has already taken effect in our recruit data.[11]

Finally, the applicant's AA scores for MOS alternatives in the job list have a positive significant effect across quarters, demonstrating that applicants tend to choose the MOS training opportunity for which they display the highest AA score. This observation has an important implication for EPAS. It suggests an existing positive person-job-match in REQUEST transactions, which was assumed in the EPAS model to be random. Consequently, for EPAS to have a significant impact on REQUEST, its effect would have to be greater than that needed if the person-job-match were in fact random (i.e., AA weights are not significantly different from zero).

As for applicant attributes (gender, education status, AFQT category and percentile score, and geographic region), there were applicant differences associated with enlistment in the Army and in preferences to choose certain types of jobs. Starting with Army enlistment (see parameters post-scripted with a "999"), overall, none of the applicant attributes consistently exerted significant effects across all four quarters. However, there were some significant differences by quarter. For example, there were significant gender differences (G_sexM999) in utilities during the Second and Third quarters, such that males (on average) exhibited a more positive utility (and preference) than females to enlist. Similarly, high school seniors (G_edS999) were less likely to join the Army compared to high school graduates during the first three quarters when school was still on going. This is not the case after the end of the school year during the fourth quarter, as evidenced by a not significant negative interaction effect. Only geographic region (G_RS999) did not produce a significant effect on applicant enlistment preference at some point during the FY. Shifting to applicant differences in MOS job preferences, applicants (on average) did differ in the utilities associated with different types of jobs. For example, males consistently tended to attribute (on average) greater utility to Electronic (G_sexM3), General Maintenance (G_sexM5), and Mechanical Maintenance (G_sexM6) jobs than did females. This trend makes sense given that historically male Army applicants generally achieve higher AA scores and demonstrate a greater propensity to enlist in these jobs than females. Similarly, consistent with the fact that they tend not to be eligible for these types of jobs, non-high school graduates tended to attribute lower utility to Skilled Technical jobs (G_edNG9) than high school graduates. Taken together, and consistent with the alternative-specific constants (discussed above), the direction and general magnitude of these parameters are consistent with previous research and observations of Army applicant job choices indicating (indirectly) that the model conforms with real-world job choice processes (and utilities).

[11] The HG incentive is given to applicants with more than 30 semester hours of college if they choose an "incentivized" MOS (i.e., these are MOS with EB/ACF incentives). However, because these MOS account for at least 75% of the 101 MOS alternatives considered in the JCM, the incentive effectively functioned in the model as an indicator for college applicants, who tend to be more selective and less likely to access. Thus, the negative HG effect. If we start with the youth population (or market that can be reached by recruiters) in our modeling, then we will be able to see the real impact of this incentive in encouraging youth to *consider and join* the Army, and different results may likely be obtained.

Table 3. Selected Alternative-Specific Constant Parameter Estimates by Quarter. Scaled for Second-Level Conditional MNL Model.

ID	MOS	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
1	11X	0.000000	0.00	0.000000	0.00	0.000000	0.00	0.000000	0.00
2	12B	-1.032514	**-2.88**	-1.205904	**-3.67**	-0.956949	**-3.93**	-1.196391	**-4.54**
3	12C	-3.648624	**-3.19**	-4.749867	**-2.82**	-3.658656	**-4.86**	-3.456503	**-4.72**
4	13B	-1.524655	**-3.32**	-2.591657	**-1.99**	-1.005380	**-3.77**	-1.780787	**-2.86**
5	13F	-2.112759	**-3.27**	-3.600447	**-2.35**	-1.572297	**-4.26**	-2.510510	**-3.45**
6	13M	-2.798734	**-3.32**	-3.613938	**-2.35**	-2.123325	**-4.48**	-3.458444	**-3.98**
7	13P	-3.065477	**-3.32**	-3.996978	**-2.45**	-2.312500	**-4.38**	-3.959124	**-4.16**
8	13R	-3.872185	**-3.29**	-4.765011	**-2.63**	-2.850153	**-4.65**	-3.780163	**-4.11**
9	13X	-2.245583	**-3.27**	-3.189995	**-2.21**	-1.637832	**-4.28**	-2.055024	**-2.56**
10	14E	-3.466895	**-3.28**	-4.535784	**-2.59**	-2.117172	**-4.36**	-2.741935	**-3.45**
11	14J	-2.794358	**-3.29**	-4.494932	**-2.58**	-2.151144	**-4.45**	-2.528426	**-3.34**
12	14R	-3.319357	**-3.34**	-4.255660	**-2.52**	-1.833978	**-4.42**	-3.374030	**-3.83**
13	14S	-2.691492	**-3.25**	-3.835277	**-2.40**	-1.994968	**-4.39**	-2.971097	**-3.54**
14	14T	-3.070878	**-3.33**	-4.348678	**-2.55**	-2.488423	**-4.59**	-3.260988	**-3.80**
15	18X	NA	**NA**	0.525125	1.45	2.226504	**4.03**	2.665860	**4.04**
16	19D	-1.492637	**-3.27**	-1.374866	**-3.69**	-1.055166	**-4.12**	-1.085599	**-4.47**
17	19K	-1.619723	**-3.30**	-1.210841	**-3.65**	-1.018792	**-4.24**	-1.283392	**-4.85**
18	27D	-0.132010	-0.26	-1.309207	-1.14	0.540499	1.13	-1.335957	-1.91
19	31C	-0.917883	-1.51	-2.512283	-1.88	-1.395378	**-2.67**	-1.775547	**-2.63**
20	31F	-1.147512	**-2.26**	-2.577982	-1.94	-0.446152	-1.17	-1.457798	**-2.24**
999	000	-1.009706	**-4.11**	-1.317931	**-4.56**	-0.903310	**-3.60**	-0.102697	-0.31

Table 4. Utility Weights and Scale Parameter Estimates by Quarter. Scaled for Second-Level Conditional MNL Model.								
	First Quarter		Second Quarter		Third Quarter		Fourth Quarter	
Parameter	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
B_Rnk	-0.011977	**-2.97**	-0.007928	**-3.24**	-0.012900	**-3.44**	-0.021405	**-3.57**
B_RrnkC	0.000386	**3.32**	0.000184	**3.40**	0.000317	**3.78**	0.000497	**3.82**
B_1sTEAb	0.053072	1.59	-0.004273	-0.23	-0.031338	-0.97	0.096952	**2.80**
B_SBd	0.077739	**2.78**	0.019529	**1.99**	0.040865	**2.09**	0.160683	**3.28**
B_SBSd	0.108585	1.33	0.068228	1.17	-0.231727	**-2.04**	-0.038425	-0.24
B_ABd	0.072682	**2.21**	0.025353	1.42	0.061606	1.54	-0.044386	-0.90
B_HGd	-0.026097	-0.93	-0.032260	-1.63	-0.059423	-1.65	-0.046162	-1.57
B_AA	0.026985	**2.90**	0.019150	**3.08**	0.045515	**3.59**	0.075155	**5.22**
G_sexM3	0.801551	**2.67**	0.379305	**2.60**	0.863203	**3.55**	0.627257	**2.90**
G_sexM5	1.025620	**2.33**	0.986495	**2.81**	2.576515	**3.95**	0.888596	**2.41**
G_sexM6	0.630517	**2.38**	0.780355	**3.41**	1.004613	**3.77**	0.744886	**2.96**
G_sexM999	-1.946523	-1.72	-2.875824	**-3.97**	-3.077038	**-3.41**	-0.048199	-0.14
G_edS999	4.140386	**3.25**	3.857095	**4.55**	2.578470	**2.64**	-0.465246	-1.24
G_RS999	0.649710	0.67	-0.225957	**-0.34**	-0.534816	-0.66	0.067626	0.22
G_edNG9	-0.823289	**-2.47**	0.000000	0.00	-0.658215	**-2.98**	-1.164770	**-3.46**

Model Fit

As for overall model fit, pseudo-R^2 values for the full JCM ranged from 0.17 (Third Quarter) to 0.23 (First Quarter). While interpretation of pseudo-R^2 values is not as straightforward as in traditional linear regression, these fit statistics compare (very) favorably to those obtained for other prediction problems in the social and applied sciences, where comparable effects sizes tend to average about .10-.15. While overall model fit is informative, fit diagnostics at the subgroup level are equally if not more important, particularly those that more directly speak to expected predictive accuracy. Fit diagnostics at the subgroup and job family levels (by quarter) are reported in Appendix C (Tables C.1. through C.4). As an orientation to the tables, the following is a summary of their contents (by column):

- "Freq" reports the number of times an MOS within the applicable job family was offered (*not* necessarily selected) to an applicant within the specified subgroup during that quarter. Note that the number reported for the special job family "Non-Acc", which represents the non-accession alternative, reflects the total number of applicants within the specified subgroup during that quarter.
- "Estimate (E)" reports the *estimated* (or expected) probability (based on the JCM) that an applicant from the applicable subgroup that would select an MOS from the specified job family during that quarter. For the Army enlistment decision (see "Non-Acc"s), these numbers reflect the estimated probability that an applicant from the applicable subgroup will elect to *not* join the Army during that quarter.
- "Actual (A)" reports the *actual* (or observed) proportion of applicants within the applicable subgroup who selected an MOS from the specified job family during that quarter. Operationally, this figure reflects the number of applicants within the applicable subgroup selecting an MOS from the specified job family divided by the number of times it was offered ("Freq") during the same quarter. For the Army enlistment decision (see "Non-Acc"s), these numbers reflect the actual (or observed)

proportion of applicants from the applicable subgroup that did *not* elect to join the Army during that quarter.

- "Diff(A-E)" reports the raw differences between the actual ["Actual(A-E)"] and estimated ["Estimate(E)"] figures by subgroup and job family within that quarter. Negative differences reflect over-prediction, while positive differences reflect under-prediction. The closer these differences are to zero the greater the JCM's accuracy in predicting applicants' job choices.
- "Ratio(E/A)" reports the ratio of the estimated ["Estimate(E)"] and actual ["Actual(A)"] figures by subgroup and job family within that quarter. This diagnostic provides information comparable to "Diff(A-E)", but facilitates comparisons across subgroups and job families. By formulating these differences as a ratio (a proportion), this diagnostic controls for MOS and job family differences in selection proportions— the magnitude of "Diff(A-E)" values is bigger for MOS opportunities that are selected more frequently. Ratios greater than 1.00 are indicative of under-prediction, while ratios less than 1.00 indicate over-prediction. The closer the ratio is to 1.00 the more accurate the JCM's predictions of applicants' job choices. In evaluating (and diagnosing) the intermediate and final forms of the JCM, we aimed for ratios between .80 and 1.20. We selected these values because they indicate that no greater than 20% of applicants' choices (as a group) are being incorrectly predicted—an error rate comparable to those of most prediction problems.

A review of Tables C.1 through C.4 indicates the following. First, in terms of predicting applicants' choices to join (or not) the Army, the performance of the JCM is strong. Across all subgroups and quarters, differences between actual and expected choices are small, as evident by "Diff(A-E)" values uniformly close to zero and "Ratio(E/A)" close to 1.00. With the exception of AFQT Cat IV applicants (for the Second and Third Quarters), for which sample sizes tend to be small, the error rates (see the "Ratio(E/A)" values) do not exceed 4%. For applicants as a whole (see Subgroup labeled "All"), the JCM is correctly predicting close to 100% of applicants' decisions to join (or not) the Army. Second, regarding applicants' MOS opportunity choices, the diagnostics indicate that the predictive efficacy of the JCM is good across subgroups and job families. With the exception of job families with MOS that are infrequently offered (e.g., Surveillance and Communication-SC) or subgroups with small sample sizes (AFQT Cat IVs) and/or combinations of the two (e.g., Female applicants for Field Artillery-FA positions), "Diff(A-E)" values are consistently close to zero across all four quarters. Similarly, while there is greater variability in "Ratio(E/A)" values than when predicting Army enlistment decisions, these values are consistently within the accepted criteria for all subgroups and job families ($.80 < \text{Ratio}(x) < 1.20$). For applicants as a whole (see Subgroup labeled "All"), these error rates do not exceed 9%, even for the less critical job families (e.g., SC). This means that overall, the JCM is correctly predicting roughly 91%+ of applicants' MOS opportunity choices across the four quarters.

Out-of-Sample Prediction

To examine the predictive performance of the estimated JCM model we carried out the same diagnostics used above for model fit on the out-of-sample observations from each quarter. Predictive performance diagnostics at the subgroup and job family level are reported by quarter

in Appendix D (Tables D.1 through D.4). Note that there are row entries in these tables with zeroes under column "Actual(A)" and undefined under column "Ratio(E/A)." These rows correspond to relatively small subgroup-job family combinations that were all included in the estimation sample.

At the overall Army level (subgroup labeled "All"), the estimated probabilities of an applicant selecting an MOS from a given job family are all relatively close to the actual percentages, with the exception of Surveillance & Communications (SC) which accounted for a very small percentage of the total opportunities. The magnitude of the differences between estimated and actual percentage for SC across all EIRB quarters is acceptable given the intended application of the JCM and total frequency SC opportunities were offered. In terms of the decision to join or not to join the Army, the differences between the expected and actual percentages are also small for all quarters.

At the subgroup level, the predictive performance remains satisfactory overall across all quarters. However, the diagnostics indicate more instances of over or under predicting outside of the desirable range (Ratio (E/A) between .80 and 1.20) even for AFQT non-Cat IV applicants. An examination of the estimated and actual percentages, however, suggests that for most of these cases the discrepancies are relatively not too large for our intended application.

In sum, the overall and subgroup diagnostics indicate that the JCM model fit is high and that it has good predictive accuracy for our application.

SIMULATING ARMY APPLICANTS' JOB CHOICES

To implement the JCM in the EPAS Simulation, we developed a procedure for simulating a randomized job choice for each applicant. As an overview, this job choice randomization procedure involves two stages. In the first stage, percentages are computed that represent the "attractiveness" (i.e., utilities) of the different job opportunities to the applicant. In the second stage, a random choice decision is then generated for the applicant using these attractivenesss percentages. As discussed previously, the choice decision generated results in the applicant either: (a) deciding to not join the Army; or (b) selecting one of the available job opportunities from their list.

The computational details and data input requirements involved in these two stages, including step-by-step instructions for implementing the procedure in the EPAS Simulation environment, are documented in the following sections. In describing the procedure, no distinction is made between REQUEST and EPAS-Enhanced REQUEST simulation conditions. This is because the computational steps in procedure are independent of the condition underlying the rank ordering of the job opportunities. To illustrate our procedure (and its implementation), an example is provided in the accompanying MS Excel workbook.

First Stage: Computing Attractiveness Percentages

The objective in the first stage is to compute attractiveness percentages for each MOS-reception date row opportunity in the job list of an applicant. These percentages become the input for the second stage, where the applicant's randomized choice decision is generated to reflect either: (a) a decision not to join the Army; or (b) the selection of a specific MOS-reception date (job) opportunity. The algorithm described below is developed around a JCM auxiliary table. The purpose of this table is to store intermediate values in the calculation of the attractiveness percentages.

Steps for Computing Attractiveness Percentages

Table 5 identifies the columns in the JCM auxiliary table relevant to computing attractiveness percentages. The rows in the auxiliary table are indexed by: (1) applicant's SSN (IND_SSN); (2) date and time search was completed (CONTRACT_DATE); and (3) the MOS and reception date (RECSTA_DT) of the job opportunity. In other words, the row dimension exactly conforms to that of the job opportunity data, with one record for each MOS-reception date opportunity in the job list of each applicant. Column ATTRACT_PCT represents the attractiveness percentage, which is the final output in this stage. Columns WGT_ACCESS through EPSCORE_TOT are intermediate values in the computation of ATTRACT_PCT. The second column in Table 5 indicates whether the value of a column in the auxiliary table will be supplied (FIXED=Y) or will be computed during the simulation (FIXED=N). Columns in the auxiliary table that are FIXED (FIXED=Y) contain "pre-computed" values based on applicant demographics, test scores, and incentives offered with the MOS opportunities in an applicant's job list. Columns containing values to be computed during the simulations (FIXED=N) depend on the ranking of opportunities in the job list.

Table 5. JCM Auxiliary Table for Computing Job Attractiveness Percentage

Column	FIXED	Description	Data Type
IND_SSN	Y	applicant's SSN	char(9)
CONTRACT_DATE	Y	date/time search was completed	date/time
MOS	Y	MOS of job opportunity	char(3)
RECSTA_DT	Y	reception date of job opportunity	date
WGT_ACCESS	Y	accession percentage weight	number(10,8)
WGT_RANK	Y	weight of rank in preference score	number(10,8)
RANK_PCT	N	rank of opportunity in percentage	number(10,8)
PSCORE_FIXED	Y	known part of preference score	number(10,8)
PSCORE_RANK	N	rank based part of preference score	number(10,8)
EPSCORE_TOT	N	total preference score	number(10,8)
ATTRACT_PCT	N	attractiveness percentage	number(10,8)

Note: Depending on how computations in the first stage are implemented, columns PSCORE_RANK and EPSCORE_TOT in the JCM auxiliary table can be made optional

The following steps describe the computations needed to obtain the ATTRACT_PCT values for the opportunities in an applicant's job list. In the expressions below, job opportunities for a given applicant are identified (or indexed) using the SSN (i) of the applicant, and the MOS (m) and reception date (d) of each opportunity.

Step 1. Compute RANK_PCT. Convert the integer rank order of each row opportunity in the job list to its percentage equivalent using the following formula:

$$R_P(i,m,d) = \frac{R_O(i,m,d)}{N(i)}$$

where

$R_O(i,m,d) =$ Integer rank order of the row opportunity identified by MOS m and reception date d in the job list of the ith applicant.

$N(i) =$ Total number of opportunities in the job list of the ith applicant.

$R_P(i,m,d) =$ Percentage rank equivalent of $R_O(i,m,d)$

Note that $R_O(i,m,d)$ will be based on the rank ordering of REQUEST or EPAS-Enhanced REQUEST conditions.

Step 2. Compute PSCORE_RANK. Compute the component of the preference score that is dependent on the rank of the job opportunity:

$$S_R(i,m,d) = 100 \times W_R(i) \times R_P(i,m,d)$$

where

$W_R(i) =$ Weight applied to percentage ranks of job opportunities of the ith applicant (WGT_RANK).

$S_R(i,m,d) =$ Rank-based component of preference score of the ith applicant for the job opportunity identified by MOS m and reception date d.

Step 3. Compute EPSCORE_TOT. Compute the exponential of total preference scores for each row opportunity in the job list:

$$E_T(i,m,d) = \exp\{S_F(i,m,d) + S_R(i,m,d)\}$$

where

$S_F(i,m,d) =$ FIXED component of preference score of the ith applicant for the job opportunity identified by MOS m and reception date d (PSCORE_FIXED).

$E_T(i,m,d) =$ Exponential of total preference score of the ith applicant for the job opportunity identified by MOS m and reception date d (EPSCORE_TOT).

Note that by using $E_T(i,m,d) = \exp\{S_F(i,m,d) + W_R(i) \times R_P(i,m,d)\}$, Step 2 can be skipped and column PSCORE_RANK dropped from the JCM auxiliary table.

Step 4. Compute ATTRACT_PCT. Convert the total preference scores of row opportunities into attractiveness percentage values using the following formulas:

$$(1) \qquad A_P(i,m,d) = W_A(i) \times \frac{E_T(i,m,d)}{E_T(i)}$$

$$(2) \qquad E_T(i) = \sum_{m,d} E_T(i,m,d)$$

where

$E_T(i) =$ Sum of exponential of total preference scores $E_T(i,m,d)$ across all row opportunities in the job list of the ith applicant.

$W_A(i) =$ Accession percentage weight for the ith applicant (WGT_ACCESS).

$A_P(i,m,d) =$ Attractiveness percentage of the ith applicant for the job opportunity identified by MOS m and reception date d (ATTRACT_PCT)

Note that the attractiveness percentage values $A_P(i,m,d)$ across opportunities in the job list of the ith applicants add up to $W_A(i)$, which generally is less than or equal to 100 percent (see additional details in the next section).

Table 6. Example JCM Auxiliary Table Rows for a Single Applicant

IND_SSN	CONTRACT_DATE	MOS	RECSTA_DT	WGT_ACCESS	WGT_RANK	RANK_PCT	PSCORE_FIXED	PSCORE_RANK	EPSCORE_TOT	ATTRACT_PCT
123456789	10/26/01	11X	11/19/01	0.92738761	-0.30852738	0.04000000	4.87461438	-0.01234110	129.31784399	0.21795323
123456789	10/26/01	13M	11/05/01	0.92738761	-0.30852738	0.08000000	2.69363153	-0.02468219	14.42480561	0.02431167
123456789	10/26/01	14E	11/12/01	0.92738761	-0.30852738	0.12000000	3.43228909	-0.03702329	29.82257933	0.05026319
123456789	10/26/01	14J	11/26/01	0.92738761	-0.30852738	0.16000000	3.22094504	-0.04936438	23.84514558	0.04018878
123456789	10/26/01	14R	11/19/01	0.92738761	-0.30852738	0.20000000	3.20961414	-0.06170548	23.28731197	0.03924860
123456789	10/26/01	14T	11/26/01	0.92738761	-0.30852738	0.24000000	2.96489904	-0.07404657	18.00865484	0.03035192
123456789	10/26/01	19D	11/05/01	0.92738761	-0.30852738	0.28000000	3.85587978	-0.08638767	43.35803811	0.07307595
123456789	10/26/01	93C	11/26/01	0.92738761	-0.30852738	0.32000000	2.62821798	-0.09872876	12.54709565	0.02114697
123456789	10/26/01	31R	11/26/01	0.92738761	-0.30852738	0.36000000	3.96649586	-0.11106986	47.24874065	0.07963337
123456789	10/26/01	63A	11/19/01	0.92738761	-0.30852738	0.40000000	2.96425564	-0.12341095	17.13022916	0.02887141
123456789	10/26/01	63M	11/05/01	0.92738761	-0.30852738	0.44000000	2.53579504	-0.13575205	11.02365033	0.01857934
123456789	10/26/01	13X	11/26/01	0.92738761	-0.30852738	0.48000000	2.67137423	-0.14809314	12.46944291	0.02101609
123456789	10/26/01	14S	11/26/01	0.92738761	-0.30852738	0.52000000	2.31764614	-0.16043424	8.64699533	0.01457371
123456789	10/26/01	35M	11/12/01	0.92738761	-0.30852738	0.56000000	2.94551118	-0.17277533	16.00235415	0.02697048
123456789	10/26/01	52D	11/19/01	0.92738761	-0.30852738	0.60000000	1.90261674	-0.18511643	5.57058633	0.00938871
123456789	10/26/01	62B	11/26/01	0.92738761	-0.30852738	0.64000000	1.23870464	-0.19745752	2.83274759	0.00477433
123456789	10/26/01	67U	11/05/01	0.92738761	-0.30852738	0.68000000	3.20701730	-0.20979862	20.02975031	0.03375829
123456789	10/26/01	68G	11/05/01	0.92738761	-0.30852738	0.72000000	1.66273864	-0.22213971	4.22322447	0.00711785
123456789	10/26/01	68H	11/26/01	0.92738761	-0.30852738	0.76000000	1.61509864	-0.23448081	3.97735821	0.00670347
123456789	10/26/01	68S	11/12/01	0.92738761	-0.30852738	0.80000000	2.72246134	-0.24682190	11.88930716	0.02003832
123456789	10/26/01	91W	11/26/01	0.92738761	-0.30852738	0.84000000	4.55841269	-0.25916300	73.64451667	0.12412100
123456789	10/26/01	55B	11/05/01	0.92738761	-0.30852738	0.88000000	2.07597963	-0.27150409	6.07678357	0.01024185
123456789	10/26/01	35Y	11/12/01	0.92738761	-0.30852738	0.92000000	2.77416449	-0.28384519	12.06512789	0.02033465
123456789	10/26/01	63G	11/12/01	0.92738761	-0.30852738	0.96000000	1.17920624	-0.29618628	2.41819153	0.00407564
123456789	10/26/01	63J	11/19/01	0.92738761	-0.30852738	1.00000000	-0.64612826	-0.30852738	0.38494468	0.00064879

Stage One Example

The following example illustrates the steps in the computation of the attractiveness percentages. Table 6 shows the rows in the completed JCM auxiliary table for a single applicant. There are a total of 25 opportunities in the job list for this applicant.

In Step 1, the integer ranks 1 through 25 were converted to their percentage equivalent (RANK_PCT) in decimal form by dividing each by 25. In Step 2, each of these rank percentages was then multiplied by -.30852738, the value of WGT_RANK, to obtain PSCORE_RANK. Note that WGT_RANK can (and will) differ across applicants, but is constant for the same applicant. The computed value of PSCORE_RANK is the component of the preference score that is dependent on rank.

Continuing with the example, in Step 3, the exponential of the sum of PSCORE_FIXED and PSCORE_RANK was calculated to obtain EPSCORE_TOT for each of the 25 job opportunities. For example, looking at the MOS 11X opportunity, EPSCORE_TOT was evaluated as $exp(4.87461438-0.01234110)$, which is equal to 129.31784399. In Step 4, EPSCORE_TOT values for all 25 opportunities of the applicant were initially converted to percentages by dividing each by their total (550.24542601). To obtain ATTRACT_PCT, each percentage was then multiplied by WGT_ACCESS (0.92738761). Note that the attractiveness percentages at the end of Step 4 add up to 0.92738761, which is equal to the value of WGT_ACCESS (as it should).

Second Stage: Generating An Applicant's Job Choice

In the second stage the goal is to generate a randomized job choice. This choice decision reflects an applicant's decision to either: (a) not join the Army; or (2) select one of the available job opportunities from their job list, using a randomization procedure that is consistent with the JCM. By incorporating a randomized component in simulating applicant job choice, the accuracy of the JCM for modeling real-world applicant decisions is enhanced. To ensure that across multiple replications an applicant's simulated job choice generally corresponds to their actual decision, this randomization procedure must produce, on the average, selection probabilities (percentages) that are equal to the attractiveness percentages of opportunities in the job list computed in Step 4 of the previous section. A chance algorithm that satisfies this requirement is described below.

Steps in Generating Applicant's Randomized Job Choice

To simplify the discussion, the applicant index i will be dropped from our notation and the MOS-reception date opportunities will be labeled by $\{O_1, O_2, \ldots, O_j, \ldots, O_N\}$, where N is the total number of opportunities in the job list of an applicant. It is not necessary for the sequence of jobs in this set to correspond to an actual rank ordering. Similarly, we will denote the attractiveness percentages computed from Section 2 by $A_P(j)$, for $j = 1, 2, \ldots, N$, in the same order as the job list sequence.

Using the preceding notations, the chance algorithm for randomly assigning an applicant to one of the jobs in $\{O_1, O_2, \ldots, O_j, O_{j+1}, \ldots, O_N\}$, given the applicant's attractiveness percentages $\{A_P(1), A_P(2), \ldots, A_P(j), \ldots, A_P(N)\}$, is described by the following steps.

Step 1. Construct Job Look-Up Intervals. Partition the unit interval (0,1) into N+1 sub-intervals or "bins":

$$(L_1,U_1],(L_2,U_2],\ldots,(L_j,U_j],\cdots,(L_N,U_N],(L_{N+1},U_{N+1}]$$

where $L_1 = 0$, $U_{N+1} = 1$, and the remaining lower and upper bounds are computed from the applicant's attractiveness percentages using:

$$U_j = \begin{cases} \sum_{h=1}^{j} A_P(h) & , j = 1,2,\ldots,N \\ 1 & , j = N+1 \end{cases}$$

$$L_j = U_{j-1}, j = 2,3,\ldots,N+1$$

Note that U_N must be equal to $1 - W_A$.

Step 2. Generate a Decision Random Number. Generate a pseudo random number D, $0 < D < 1$.

Step 3. Simulate Applicant's Choice Decision. Using the random number D, compute the job index value j_D using the rule:

$$\begin{aligned} j_D &= \min_{D<U_j}\{j \mid j = 1,2,\ldots,N\} \\ &= \max_{D>L_j} z\{j \mid j = 1,2,\ldots,N\} \end{aligned}$$

The first expression states that j_D indexes the job associated with the first upper bound that is greater than or equal to D (i.e., U_{j_D} is the minimum among U_js above D). Similarly, the second expression states that j_D indexes the job associated with the last lower bound that is less than D (i.e., L_{j_D} is the maximum among L_js below D). When programming to implement this step, it may be more convenient to use one form over the other depending on the available routines.

The job index value j_D is interpreted in terms of the applicant simulated choice decision as follows:

Access: If $j_D < N$, the applicant chooses job O_{j_D}.
Not Access: If $j_D = N+1$, the applicant decides not to access or join the Army.

Alternatively, the applicant's simulated choice decision can also be expressed directly in terms of the random number D as follows:

Access: If $U_{j_D - 1} < D < U_{j_D}$, the applicant chooses job O_{j_D}.
Not Access: If $D > U_N$, the applicant decides not to access or join the Army.

The following comments pertain to actual EPAS simulation runs. Under pure REQUEST condition, the attractiveness percentages computed in Step 4 of Section 2 will remain constant across replications of the simulation; that is, $A_P(i,m,d)$ is constant for specified values of i, m, and d. However, under EPAS-Enhance REQUEST condition, attractiveness percentages for a given applicant can vary across replications. These percentages will depend on EPAS rank ordering of opportunities for the week (or EPAS optimization period) of the search date, which itself is a function of all simulated choice decisions during the period preceding the search week of an applicant.

Stage Two Example

The following discussion continues the example introduced in the preceding section. At the end of that discussion, attractiveness percentages were obtained for each opportunity in the job list of the applicant. The 25 opportunities in the list are again shown in Table 7, along with two columns for the lower and upper bounds of the 26 look-up intervals. The 26th interval corresponds to the choice decision not to join the Army (not access), which is represented by the value 000 at the bottom of the MOS column.

The 26 look-up intervals defined by the last two columns in Table 7 were constructed using the formulas in Step 1. First, the upper bound of the interval for the first opportunity in the job sequence (MOS 11X) was set to 0.21795323, the attractiveness percentage of the first opportunity obtained from Table 6. Then the upper bounds of the remaining opportunities were computed by adding their respective attractiveness percentages to the upper bound of the preceding opportunity in the job sequence. For example, attractiveness of the second opportunity is 0.02431167, thus its upper bound is equal to 0.02431167+0.21795323 or 0.24226490. The lower bound for the first opportunity was set to zero, while lower bounds for all other opportunities were set respectively to the upper bounds of the preceding opportunities in the job sequence.

After constructing the look-up table above, job choices can be simulated for the applicant using Steps 2 and 3 of the second stage. This is illustrated as follows using the lower bound version of Step 3. Suppose the decision random number D generated in Step 2 is equal to 0.36596490. Going down column LOWER_BND in Table 7, the maximum lower bound that is less than 0.36596490 was 0.33271687, which corresponds to the fifth job in the list (MOS 14 R). This would be the simulated job choice of the applicant for the given realization of the random number D.

Table 7. Example Job Look-Up Intervals for Generating Choice Decisions

JOB_IDX	IND_SSN	CONTRACT_DATE	MOS	RECSTA_DT	LOWER_BND	UPPER_BND
1	123456789	10/26/01	11X	11/19/01	0.00000000	0.21795323
2	123456789	10/26/01	13M	11/05/01	0.21795323	0.24226490
3	123456789	10/26/01	14E	11/12/01	0.24226490	0.29252809
4	123456789	10/26/01	14J	11/26/01	0.29252809	0.33271687
5	123456789	10/26/01	14R	11/19/01	0.33271687	0.37196547
6	123456789	10/26/01	14T	11/26/01	0.37196547	0.40231739
7	123456789	10/26/01	19D	11/05/01	0.40231739	0.47539334
8	123456789	10/26/01	93C	11/26/01	0.47539334	0.49654031
9	123456789	10/26/01	31R	11/26/01	0.49654031	0.57617367
10	123456789	10/26/01	63A	11/19/01	0.57617367	0.60504509
11	123456789	10/26/01	63M	11/05/01	0.60504509	0.62362443
12	123456789	10/26/01	13X	11/26/01	0.62362443	0.64464051
13	123456789	10/26/01	14S	11/26/01	0.64464051	0.65921422
14	123456789	10/26/01	35M	11/12/01	0.65921422	0.68618471
15	123456789	10/26/01	52D	11/19/01	0.68618471	0.69557341
16	123456789	10/26/01	62B	11/26/01	0.69557341	0.70034775
17	123456789	10/26/01	67U	11/05/01	0.70034775	0.73410603
18	123456789	10/26/01	68G	11/05/01	0.73410603	0.74122388
19	123456789	10/26/01	68H	11/26/01	0.74122388	0.74792735
20	123456789	10/26/01	68S	11/12/01	0.74792735	0.76796568
21	123456789	10/26/01	91W	11/26/01	0.76796568	0.89208668
22	123456789	10/26/01	55B	11/05/01	0.89208668	0.90232853
23	123456789	10/26/01	35Y	11/12/01	0.90232853	0.92266318
24	123456789	10/26/01	63G	11/12/01	0.92266318	0.92673882
25	123456789	10/26/01	63J	11/19/01	0.92673882	0.92738761
26	123456789	10/26/01	000		0.92738761	1.00000000

Alternative MOS choices are shown in Table 8 for different realizations of the decision random number D using the look-up intervals in Table 7. Since Table 7 was FIXED here, this section of the example can only apply to simulation replications for REQUEST condition. Note that in simulation replication number 17, the applicant "chooses" not to join the Army -- as with the REQUEST transaction data, the applicant would not have a reservation for this replication.

Table 8. Example Job Choice Decisions for Realizations of *D*

SIM_REP	D_RAND	CHOICE	SIM_REP	D_RAND	CHOICE	SIM_REP	D_RAND	CHOICE
1	0.36596490	14R	11	0.73552556	68G	11	0.67483575	35M
2	0.25609965	14E	12	0.23393994	13M	22	0.11551405	11X
3	0.01446337	11X	13	0.62987706	13X	23	0.54983242	31R
4	0.24730711	14E	14	0.41649715	19D	24	0.65373572	14S
5	0.01710986	11X	15	0.58733379	63A	25	0.25938727	14E
6	0.59452253	63A	16	0.21763324	11X	26	0.82558274	91W
7	0.42728675	19D	17	0.92913210	000	27	0.37955547	14T
8	0.90603971	35Y	18	0.04151490	11X	28	0.53611325	31R
9	0.37711992	14T	19	0.02839122	11X	29	0.69975815	62B
10	0.80787759	91W	20	0.77322239	91W	30	0.06908547	11X

Example Excel Workbook

The accompanying Excel workbook contains the data and tables used in the examples presented in this document to illustrate the job choice randomization procedure. There are a total of four worksheets in the workbook. The following is a brief description of each:

- OppDATA. This worksheet contains 25 job opportunities for a single applicant (only columns used in the procedure are shown). The column RANK can represent the job ordering based on the REQUEST or EPAS-Enhanced REQUEST conditions. Note that rows need not be sorted by RANK.
- AuxTBL. This worksheet represents the JCM auxiliary table and calculations described in the "First Stage: Computing Attractiveness Percentages" section (see Tables 5 and 6). Columns in black font correspond to supplied values, while columns in blue font were computed in the worksheet using Excel functions/formulas.
- LookUpTBL. This worksheet is an example of the look-up table and chance algorithm described in the "Second Stage: Generating An Applicant's Job Choice" section (see Table 7). For this particular example, the lower bound version of the rule given in Step 3 of the algorithm was implemented.
- SimTBL. The rows in this worksheet show the result of 30 separate and independent simulation replications for the single applicant (see Table 8). Values under D_RAND were generated using Excel rand() function. As a reminder, the special MOS value equal to 000 indicates that the applicant decided to not join the Army.

SIMULATION RESULTS

IND_SSN	CONTRACT_DATE	SIM_REP	D_RAND	CHOICE
123456789	10/26/2001	1	0.36596490	14R
123456789	10/26/2001	2	0.25609965	14E
123456789	10/26/2001	3	0.01446337	11X
123456789	10/26/2001	4	0.24730711	14E
123456789	10/26/2001	5	0.01710986	11X
123456789	10/26/2001	6	0.59452253	63A
123456789	10/26/2001	7	0.42728675	19D
123456789	10/26/2001	8	0.90603971	35Y
123456789	10/26/2001	9	0.37711992	14T
123456789	10/26/2001	10	0.80787759	91W
123456789	10/26/2001	11	0.73552556	68G
123456789	10/26/2001	12	0.23393994	13M
123456789	10/26/2001	13	0.62987706	13X
123456789	10/26/2001	14	0.41649715	19D
123456789	10/26/2001	15	0.58733379	63A
123456789	10/26/2001	16	0.21763324	11X
123456789	10/26/2001	17	0.92913210	000
123456789	10/26/2001	18	0.04151490	11X
123456789	10/26/2001	19	0.02839122	11X
123456789	10/26/2001	20	0.77322239	91W
123456789	10/26/2001	21	0.67483575	35M
123456789	10/26/2001	22	0.11551405	11X
123456789	10/26/2001	23	0.54983242	31R
123456789	10/26/2001	24	0.65373572	14S
123456789	10/26/2001	25	0.25938727	14E
123456789	10/26/2001	26	0.82558274	91W
123456789	10/26/2001	27	0.37955547	14T
123456789	10/26/2001	28	0.53611325	31R
123456789	10/26/2001	29	0.69975815	62B
123456789	10/26/2001	30	0.06908547	11X

AUXILIARY TABLE

IND_SSN	CONTRACT_DATE	MOS	RECSTA_DT	WGT_ACCESS	WGT_RANK	*blue font* RANK_PCT	PSCORE_FIXED	*blue font* PSCORE_RANK	*blue font* EPSCORE_TOT	*blue font* ATTRACT_PCT
123456789	10/26/2001	11X	11/19/01	0.92738761	-0.30852738	0.04000000	4.87461438	-0.01234110	129.31784399	0.21795323
123456789	10/26/2001	13M	11/05/01	0.92738761	-0.30852738	0.08000000	2.69363153	-0.02468219	14.42480561	0.02431167
123456789	10/26/2001	14E	11/12/01	0.92738761	-0.30852738	0.12000000	3.43228909	-0.03702329	29.82257933	0.05026319
123456789	10/26/2001	14J	11/26/01	0.92738761	-0.30852738	0.16000000	3.22094504	-0.04936438	23.84514558	0.04018878
123456789	10/26/2001	14R	11/19/01	0.92738761	-0.30852738	0.20000000	3.20961414	-0.06170548	23.28731197	0.03924860
123456789	10/26/2001	14T	11/26/01	0.92738761	-0.30852738	0.24000000	2.96489904	-0.07404657	18.00865484	0.03035192
123456789	10/26/2001	19D	11/05/01	0.92738761	-0.30852738	0.28000000	3.85587978	-0.08638767	43.35803811	0.07307595
123456789	10/26/2001	93C	11/26/01	0.92738761	-0.30852738	0.32000000	2.62821798	-0.09872876	12.54709565	0.02114697
123456789	10/26/2001	31R	11/26/01	0.92738761	-0.30852738	0.36000000	3.96649586	-0.11106986	47.24874065	0.07963337
123456789	10/26/2001	63A	11/19/01	0.92738761	-0.30852738	0.40000000	2.96425564	-0.12341095	17.13022916	0.02887141
123456789	10/26/2001	63M	11/05/01	0.92738761	-0.30852738	0.44000000	2.53579504	-0.13575205	11.02365033	0.01857934
123456789	10/26/2001	13X	11/26/01	0.92738761	-0.30852738	0.48000000	2.67137423	-0.14809314	12.46944291	0.02101609
123456789	10/26/2001	14S	11/26/01	0.92738761	-0.30852738	0.52000000	2.31764614	-0.16043424	8.64699533	0.01457371
123456789	10/26/2001	35M	11/12/01	0.92738761	-0.30852738	0.56000000	2.94551118	-0.17277533	16.00235415	0.02697048
123456789	10/26/2001	52D	11/19/01	0.92738761	-0.30852738	0.60000000	1.90261674	-0.18511643	5.57058633	0.00938871
123456789	10/26/2001	62B	11/26/01	0.92738761	-0.30852738	0.64000000	1.23870464	-0.19745752	2.83274759	0.00477433
123456789	10/26/2001	67U	11/05/01	0.92738761	-0.30852738	0.68000000	3.20701730	-0.20979862	20.02975031	0.03375829
123456789	10/26/2001	68G	11/05/01	0.92738761	-0.30852738	0.72000000	1.66273864	-0.22213971	4.22322447	0.00711785
123456789	10/26/2001	68H	11/26/01	0.92738761	-0.30852738	0.76000000	1.61509864	-0.23448081	3.97735821	0.00670347
123456789	10/26/2001	68S	11/12/01	0.92738761	-0.30852738	0.80000000	2.72246134	-0.24682190	11.88930716	0.02003832
123456789	10/26/2001	91W	11/26/01	0.92738761	-0.30852738	0.84000000	4.55841269	-0.25916300	73.64451667	0.12412100
123456789	10/26/2001	55B	11/05/01	0.92738761	-0.30852738	0.88000000	2.07597963	-0.27150409	6.07678357	0.01024185
123456789	10/26/2001	35Y	11/12/01	0.92738761	-0.30852738	0.92000000	2.77416449	-0.28384519	12.06512789	0.02033465
123456789	10/26/2001	63G	11/12/01	0.92738761	-0.30852738	0.96000000	1.17920624	-0.29618628	2.41819153	0.00407564
123456789	10/26/2001	63J	11/19/01	0.92738761	-0.30852738	1.00000000	-0.64612826	-0.30852738	0.38494468	0.00064879

SUM_EPSCORE_TOT= **550.24542601**

LOOK-UP TABLE

IND_SSN	CONTRACT_DATE	MOS	RECSTA_DT	JOB_IDX	LOWER_BND	UPPER_BND
123456789	10/26/2001	11X	11/19/2001	1	0.00000000	0.21795323
123456789	10/26/2001	13M	11/05/2001	2	0.21795323	0.24226490
123456789	10/26/2001	14E	11/12/2001	3	0.24226490	0.29252809
123456789	10/26/2001	14J	11/26/2001	4	0.29252809	0.33271687
123456789	10/26/2001	14R	11/19/2001	5	0.33271687	0.37196547
123456789	10/26/2001	14T	11/26/2001	6	0.37196547	0.40231739
123456789	10/26/2001	19D	11/05/2001	7	0.40231739	0.47539334
123456789	10/26/2001	93C	11/26/2001	8	0.47539334	0.49654031
123456789	10/26/2001	31R	11/26/2001	9	0.49654031	0.57617367
123456789	10/26/2001	63A	11/19/2001	10	0.57617367	0.60504509
123456789	10/26/2001	63M	11/05/2001	11	0.60504509	0.62362443
123456789	10/26/2001	13X	11/26/2001	12	0.62362443	0.64464051
123456789	10/26/2001	14S	11/26/2001	13	0.64464051	0.65921422
123456789	10/26/2001	35M	11/12/2001	14	0.65921422	0.68618471
123456789	10/26/2001	52D	11/19/2001	15	0.68618471	0.69557341
123456789	10/26/2001	62B	11/26/2001	16	0.69557341	0.70034775
123456789	10/26/2001	67U	11/05/2001	17	0.70034775	0.73410603
123456789	10/26/2001	68G	11/05/2001	18	0.73410603	0.74122388
123456789	10/26/2001	68H	11/26/2001	19	0.74122388	0.74792735
123456789	10/26/2001	68S	11/12/2001	20	0.74792735	0.76796568
123456789	10/26/2001	91W	11/26/2001	21	0.76796568	0.89208668
123456789	10/26/2001	55B	11/05/2001	22	0.89208668	0.90232853
123456789	10/26/2001	35Y	11/12/2001	23	0.90232853	0.92266318
123456789	10/26/2001	63G	11/12/2001	24	0.92266318	0.92673882
123456789	10/26/2001	63J	11/19/2001	25	0.92673882	0.92738761
123456789	10/26/2001	000		26	0.92738761	1.00000000

SIMULATION RESULTS

IND_SSN	CONTRACT_DATE	SIM_REP	D_RAND	CHOICE
123456789	10/26/2001	1	0.36596490	14R
123456789	10/26/2001	2	0.25609965	14E
123456789	10/26/2001	3	0.01446337	11X
123456789	10/26/2001	4	0.24730711	14E
123456789	10/26/2001	5	0.01710986	11X
123456789	10/26/2001	6	0.59452253	63A
123456789	10/26/2001	7	0.42728675	19D
123456789	10/26/2001	8	0.90603971	35Y
123456789	10/26/2001	9	0.37711992	14T
123456789	10/26/2001	10	0.80787759	91W
123456789	10/26/2001	11	0.73552556	68G
123456789	10/26/2001	12	0.23393994	13M
123456789	10/26/2001	13	0.62987706	13X
123456789	10/26/2001	14	0.41649715	19D
123456789	10/26/2001	15	0.58733379	63A
123456789	10/26/2001	16	0.21763324	11X
123456789	10/26/2001	17	0.92913210	000
123456789	10/26/2001	18	0.04151490	11X
123456789	10/26/2001	19	0.02839122	11X
123456789	10/26/2001	20	0.77322239	91W
123456789	10/26/2001	21	0.67483575	35M
123456789	10/26/2001	22	0.11551405	11X
123456789	10/26/2001	23	0.54983242	31R
123456789	10/26/2001	24	0.65373572	14S
123456789	10/26/2001	25	0.25938727	14E
123456789	10/26/2001	26	0.82558274	91W
123456789	10/26/2001	27	0.37955547	14T
123456789	10/26/2001	28	0.53611325	31R
123456789	10/26/2001	29	0.69975815	62B
123456789	10/26/2001	30	0.06908547	11X

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APPENDIX A: MOS ALTERNATIVES

Table A.1. JCM Alternative MOS Configuration

Alternative	MOS	Alternative	MOS
1	11X	54	77F
2	12B	55	82C
3	12C	56	88H
4	13B	57	88M
5	13F	58	88N
6	13M	59	91K
7	13P	60	91W
8	13R	61	92A
9	13X	62	92G
10	14E	63	92M
11	14J	64	92R
12	14R	65	92S
13	14S	66	92Y
14	14T	67	93C
15	18X	68	93P
16	19D	69	95B
17	19K	70	95C
18	27D	71	96B
19	31C	72	96H
20	31F	73	98C
21	31L	74	98H
22	31P	75	98J
23	31R	76	98K
24	31S	77	98X
25	31U	78	(AD1) 73C,73D
26	33W	79	(AD2) 75B,75F
27	35E	80	(AM1) 67D,67S,68F,68N,
28	51B		68X
29	52C	81	(AM2) 68B,68D,68H
30	52D	82	(AM3) 68S,68Y
31	54B	83	(EL1) 27E,35D
32	55B	84	(EL2) 35F,35J,35L,39B
33	55D	85	(EL3) 27M,27X
34	56M	86	(EL4) 27T,35H,35R,35Y
35	62B	87	(EL5) 35M,35N
36	62E	88	(FA1) 13C,13D,13E,93F
37	63A	89	(GE1) 51K,51M,51R,51T
38	63B	90	(GE2) 62F,62H,62J
39	63G	91	(MD1) 91C,91D,91E,91G,
40	63H		91H,91J,91M,91P,
41	63J		91T,91V,91X
42	63M	92	(MD2) 91Q,91R,91S
43	63S	93	(MI1) 96U,97B
44	63W	94	(MI2) 96D,96R,97E
45	63Y	95	(MM1) 44B,44E
46	67R	96	(MM2) 45B,45G,45K
47	67T	97	(MM3) 45D,63D
48	67U	98	(PA1) 37F,46Q,46R
49	68G	99	(PW1) 77L,77W
50	71L	100	(TE1) 81L,81T,82D
51	74B	101	(TS1) 88K,88L
52	74C	102	(VS1) 25M,25R,25V
53	75H	999	(000) Non-Accession

APPENDIX B: JCM PARAMETER ESTIMATES

Table B.1. Alternative-Specific Constant Parameter Estimates by Quarter

Alternative		First Quarter		Second Quarter		Third Quarter		Fourth Quarter	
ID	MOS	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
1	11X	0.000000	FIXED	0.000000	FIXED	0.000000	FIXED	0.000000	FIXED
2	12B	-0.140107	**-2.88**	-0.146416	**-3.67**	-0.172604	**-3.93**	-0.765366	**-4.54**
3	12C	-0.495100	**-3.19**	-0.576711	**-2.82**	-0.659907	**-4.86**	-2.211224	**-4.72**
4	13B	-0.206888	**-3.32**	-0.314669	**-1.99**	-0.181339	**-3.77**	-1.139220	**-2.86**
5	13F	-0.286691	**-3.27**	-0.437152	**-2.35**	-0.283593	**-4.26**	-1.606045	**-3.45**
6	13M	-0.379774	**-3.32**	-0.438790	**-2.35**	-0.382982	**-4.48**	-2.212466	**-3.98**
7	13P	-0.415970	**-3.32**	-0.485298	**-2.45**	-0.417103	**-4.38**	-2.532765	**-4.16**
8	13R	-0.525436	**-3.29**	-0.578549	**-2.63**	-0.514079	**-4.65**	-2.418278	**-4.11**
9	13X	-0.304714	**-3.27**	-0.387317	**-2.21**	-0.295414	**-4.28**	-1.314658	**-2.56**
10	14E	-0.470440	**-3.28**	-0.550717	**-2.59**	-0.381872	**-4.36**	-1.754094	**-3.45**
11	14J	-0.379180	**-3.29**	-0.545757	**-2.58**	-0.387999	**-4.45**	-1.617506	**-3.34**
12	14R	-0.450420	**-3.34**	-0.516706	**-2.52**	-0.330792	**-4.42**	-2.158464	**-3.83**
13	14S	-0.365222	**-3.25**	-0.465664	**-2.40**	-0.359830	**-4.39**	-1.900696	**-3.54**
14	14T	-0.416703	**-3.33**	-0.528000	**-2.55**	-0.448834	**-4.59**	-2.086147	**-3.80**
15	18X	NA	**NA**	0.063759	1.45	0.401592	**4.03**	1.705427	**4.04**
16	19D	-0.202543	**-3.27**	-0.166931	**-3.69**	-0.190319	**-4.12**	-0.694489	**-4.47**
17	19K	-0.219788	**-3.30**	-0.147016	**-3.65**	-0.183758	**-4.24**	-0.821023	**-4.85**
18	27D	-0.017913	-0.26	-0.158959	-1.14	0.097489	1.13	-0.854650	-1.91
19	31C	-0.124552	-1.51	-0.305032	-1.88	-0.251683	**-2.67**	-1.135868	**-2.63**
20	31F	-0.155712	**-2.26**	-0.313009	-1.94	-0.080472	-1.17	-0.932595	**-2.24**
21	31L	-0.334156	**-3.05**	-0.435286	**-2.31**	-0.371854	**-3.83**	-1.921794	**-3.68**
22	31P	-0.228902	**-2.60**	-0.371192	**-2.11**	0.014423	0.17	-0.779893	-1.87
23	31R	-0.201327	**-2.63**	-0.337383	**-2.03**	-0.203803	**-2.87**	-1.112408	**-2.66**
24	31S	-0.084691	-1.41	-0.259334	-1.70	-0.060452	-0.89	-0.312503	-0.79
25	31U	-0.181991	**-2.41**	-0.322437	**-1.97**	-0.194566	**-2.87**	-1.126257	**-2.63**
26	33W	-0.194899	**-2.39**	-0.342980	**-2.01**	-0.230478	**-2.73**	-1.102849	**-2.52**
27	35E	-0.255244	**-2.73**	-0.417017	**-2.25**	-0.244625	**-2.93**	-1.368707	**-2.95**
28	51B	-0.450032	**-3.08**	-0.550751	**-2.54**	-0.609410	**-4.26**	-1.694098	**-3.35**
29	52C	-0.511439	**-3.26**	-0.674564	**-2.79**	-0.427169	**-4.20**	-2.406377	**-3.98**
30	52D	-0.497865	**-3.29**	-0.627608	**-2.72**	-0.365494	**-4.11**	-2.153444	**-3.85**
31	54B	-0.331503	**-3.27**	-0.387764	**-2.21**	-0.161032	**-2.73**	-1.528399	**-3.38**
32	55B	-0.319738	**-2.77**	-0.485556	**-2.31**	-0.662998	**-3.92**	-2.337218	**-3.77**
33	55D	-0.389732	**-2.98**	-0.535481	**-2.43**	-0.751067	**-4.34**	-2.787473	**-4.17**
34	56M	-0.158115	**-2.08**	-0.268967	-1.71	0.341917	**2.91**	-1.441178	**-2.98**
35	62B	-0.575859	**-3.31**	-0.670085	**-2.78**	-0.513232	**-4.41**	-2.486239	**-3.93**
36	62E	-0.345543	**-2.96**	-0.527712	**-2.47**	-0.639442	**-4.20**	-2.395016	**-3.92**
37	63A	-0.454120	**-3.26**	-0.633075	**-2.72**	-0.485042	**-4.40**	-2.329227	**-3.94**
38	63B	-0.363260	**-3.23**	-0.446747	**-2.37**	-0.222184	**-3.52**	-1.434051	**-3.16**
39	63G	-0.639343	**-3.27**	-0.682207	**-2.80**	-0.535016	**-4.43**	-2.469840	**-4.03**
40	63H	-0.584212	**-3.34**	-0.655828	**-2.77**	-0.500972	**-4.55**	-2.223479	**-3.87**
41	63J	-0.681050	**-3.31**	-0.690747	**-2.80**	-0.557423	**-4.41**	-2.703770	**-4.14**
42	63M	-0.516565	**-3.25**	-0.646712	**-2.75**	-0.474416	**-4.46**	-2.519895	**-4.03**
43	63S	-0.464980	**-3.23**	-0.489874	**-2.45**	-0.385812	**-4.10**	-1.973796	**-3.69**
44	63W	-0.406710	**-3.22**	-0.536959	**-2.56**	-0.370523	**-4.07**	-1.895563	**-3.67**
45	63Y	-0.565686	**-3.32**	-0.665395	**-2.78**	-0.488271	**-4.58**	-2.237992	**-3.89**
46	67R	-0.294693	**-2.98**	-0.502330	**-2.48**	-0.333218	**-3.65**	-0.842526	**-1.98**
47	67T	-0.251185	**-2.80**	-0.410374	**-2.26**	-0.146066	**-2.28**	-0.892822	**-2.10**
48	67U	-0.395788	**-3.14**	-0.561817	**-2.60**	-0.308608	**-3.59**	-1.621313	**-3.27**
49	68G	-0.557226	**-3.26**	-0.639312	**-2.73**	-0.445261	**-4.16**	-2.261307	**-3.86**
50	71L	-0.059541	-1.19	-0.171022	-1.28	-0.032876	-0.55	-0.809398	**-2.12**

Table B.1. Alternative-Specific Constant Parameter Estimates by Quarter (continued)

Alternative		First Quarter		Second Quarter		Third Quarter		Fourth Quarter	
ID	MOS	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
51	74B	0.147538	**2.29**	-0.076685	-0.64	0.178384	**2.00**	-0.287401	-0.80
52	74C	-0.210514	**-2.44**	-0.359503	**-2.09**	-0.203380	**-2.88**	-1.283282	**-2.87**
53	75H	-0.061854	-1.09	-0.222583	-1.53	0.005808	0.08	-0.948316	**-2.32**
54	77F	-0.261181	**-3.28**	-0.361235	**-2.15**	-0.135329	**-3.55**	-1.422208	**-3.33**
55	82C	-0.534063	**-3.27**	-0.540546	**-2.54**	-0.508387	**-4.59**	-2.356341	**-4.03**
56	88H	-0.396827	**-3.24**	-0.472366	**-2.42**	-0.329119	**-3.93**	-1.543074	**-3.28**
57	88M	-0.289764	**-3.17**	-0.328297	**-2.01**	-0.199772	**-3.52**	-1.029922	**-2.56**
58	88N	-0.092068	-1.33	-0.408341	**-2.13**	-0.154784	-1.14	-1.336923	**-2.88**
59	91K	-0.121697	**-2.33**	-0.162846	-1.25	0.085473	1.14	-0.465224	-1.20
60	91W	-0.158146	**-2.63**	-0.155347	-1.22	-0.007673	-0.16	-0.553832	-1.58
61	92A	-0.047844	-0.86	-0.220029	-1.56	-0.070299	-1.34	-0.822696	**-2.16**
62	92G	-0.295858	**-3.32**	-0.392124	**-2.25**	-0.263738	**-4.43**	-1.493208	**-3.38**
63	92M	-0.388235	**-3.07**	-0.366079	**-1.98**	-0.242077	-1.70	-1.892917	**-3.58**
64	92R	-0.342194	**-3.29**	-0.502654	**-2.50**	-0.322158	**-4.30**	-1.885122	**-3.71**
65	92S	-0.396295	**-3.13**	-0.428094	**-2.28**	-0.426375	**-3.78**	-2.193055	**-3.84**
66	92Y	-0.033240	-0.79	-0.198565	-1.46	-0.123564	**-2.55**	-0.897698	**-2.33**
67	93C	-0.464959	**-3.32**	-0.558644	**-2.61**	-0.469889	**-4.33**	-1.744156	**-3.55**
68	93P	-0.328471	**-3.00**	-0.268377	-1.73	-0.151062	-1.75	-1.212605	**-2.76**
69	95B	-0.206871	**-3.01**	-0.279660	-1.85	-0.086432	**-2.01**	-0.522400	-1.54
70	95C	-0.597194	**-3.30**	-0.629843	**-2.73**	-0.482948	**-4.42**	-2.108626	**-3.91**
71	96B	0.115599	1.77	-0.157022	-1.18	0.110666	1.40	-0.390047	-1.04
72	96H	-0.285927	**-3.09**	-0.388852	**-2.20**	-0.287905	**-3.07**	-1.541499	**-3.18**
73	98C	-0.316448	**-3.11**	-0.418358	**-2.29**	-0.243895	**-3.22**	-1.551696	**-3.40**
74	98H	-0.485811	**-3.27**	-0.541645	**-2.56**	-0.516668	**-4.52**	-2.338416	**-4.09**
75	98J	-0.293389	**-3.09**	-0.358325	**-2.10**	-0.132691	-1.95	-1.564528	**-3.15**
76	98K	-0.354209	**-3.02**	-0.531642	**-2.53**	-0.316415	**-3.56**	-2.024493	**-3.79**
77	98X	0.169918	**2.32**	0.155872	1.58	0.381557	**3.80**	0.922686	**2.19**
78	AD1	-0.093330	-1.12	-0.127544	-0.82	-0.108693	-1.31	-0.847271	**-2.07**
79	AD2	-0.100154	-1.49	-0.154140	-1.16	-0.046697	-0.64	-0.957133	**-2.38**
80	AM1	-0.405439	**-3.13**	-0.526614	**-2.52**	-0.327735	**-3.64**	-1.352214	**-2.91**
81	AM2	-0.457977	**-3.21**	-0.614123	**-2.69**	-0.333059	**-3.72**	-1.821596	**-3.48**
82	AM3	-0.447347	**-3.19**	-0.575207	**-2.62**	-0.286301	**-3.30**	-1.604989	**-3.24**
83	EL1	-0.462445	**-3.14**	-0.586655	**-2.63**	-0.569539	**-4.40**	-1.994104	**-3.66**
84	EL2	-0.331652	**-2.92**	-0.428985	**-2.28**	-0.247439	**-2.89**	-1.240077	**-2.72**
85	EL3	-0.547072	**-3.17**	-0.653817	**-2.74**	-0.607658	**-4.51**	-2.651061	**-4.19**
86	EL4	-0.432345	**-3.13**	-0.495506	**-2.45**	-0.360989	**-3.70**	-1.801613	**-3.49**
87	EL5	-0.411804	**-3.10**	-0.571936	**-2.60**	-0.414541	**-3.95**	-1.841014	**-3.51**
88	FA1	-0.394492	**-2.83**	-0.408074	**-2.19**	-0.357360	**-4.16**	-1.920122	**-3.75**
89	GE1	-0.451610	**-3.09**	-0.595829	**-2.58**	-0.516447	**-4.36**	-1.965759	**-3.57**
90	GE2	-0.508666	**-3.14**	-0.630420	**-2.62**	-0.855872	**-4.58**	-2.787292	**-4.22**
91	MD1	-0.230080	**-3.00**	-0.271103	-1.79	-0.083733	-1.46	-0.956490	**-2.43**
92	MD2	-0.219325	**-2.77**	-0.338773	**-2.03**	-0.065448	-0.96	-1.215833	**-2.77**
93	MI1	-0.305665	**-2.96**	-0.180606	-1.29	0.111301	1.41	-0.589841	-1.48
94	MI2	-0.182873	**-2.66**	-0.327408	**-1.99**	-0.160152	**-2.29**	-1.159399	**-2.68**
95	MM1	-0.522227	**-3.23**	-0.619509	**-2.67**	-0.592637	**-4.58**	-2.416817	**-3.89**
96	MM2	-0.546496	**-3.19**	-0.631461	**-2.72**	-0.537425	**-4.42**	-2.513423	**-4.08**
97	MM3	-0.791066	**-3.30**	-0.877795	**-3.01**	-0.739877	**-4.75**	-3.363766	**-4.45**
98	PA1	0.128144	1.64	-0.038525	-0.30	0.075406	0.70	-1.092372	**-2.44**
99	PW1	-0.340156	**-3.05**	-0.457278	**-2.36**	-0.370239	**-3.89**	-2.197317	**-3.94**
100	TE1	-0.357425	**-3.02**	-0.446044	**-2.35**	-0.328980	**-3.65**	-2.077871	**-3.87**
101	TS1	-0.333689	**-2.56**	-0.463253	**-2.36**	-0.323622	**-3.86**	-1.628818	**-3.21**
102	VS1	-0.123101	-1.65	-0.168930	-1.14	0.142695	1.46	-1.084590	**-2.39**
999	0	-1.213891	**-4.11**	-1.537020	**-4.56**	-1.198903	**-3.60**	-0.191798	-0.31

Table B.2. Utility Weights and Scale Parameter Estimates by Quarter

Parameter	First Quarter		Second Quarter		Third Quarter		Fourth Quarter	
	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat	Estimate	T-stat
B_Rnk	-0.001625	**-2.97**	-0.001554	**-3.24**	-0.002327	**-3.44**	-0.013694	**-3.57**
B_RrnkC	0.000052	**3.32**	0.000036	**3.40**	0.000057	**3.78**	0.000318	**3.82**
B_lsTEAb	0.007202	1.59	-0.000837	-0.23	-0.005652	-0.97	0.062023	**2.80**
B_SBd	0.010549	**2.78**	0.003827	**1.99**	0.007371	**2.09**	0.102794	**3.28**
B_SBSd	0.014734	1.33	0.013372	1.17	-0.041796	**-2.04**	-0.024582	-0.24
B_Abd	0.009863	**2.21**	0.004969	1.42	0.011112	1.54	-0.028395	-0.90
B_HGd	-0.003541	-0.93	-0.006322	-1.63	-0.010718	-1.65	-0.029531	-1.57
B_AA	0.003662	**2.90**	0.003753	**3.08**	0.008209	**3.59**	0.048079	**5.22**
G_sexM2	0.000000	FIXED	-0.173337	-1.36	0.000000	FIXED	-0.281300	-0.88
G_sexM3	0.108766	**2.67**	0.074339	**2.60**	0.155695	**3.55**	0.401274	**2.90**
G_sexM5	0.139172	**2.33**	0.193341	**2.81**	0.464723	**3.95**	0.568460	**2.41**
G_sexM6	0.085558	**2.38**	0.152940	**3.41**	0.181201	**3.77**	0.476525	**2.96**
G_sexM7	0.000000	FIXED	0.000000	0.00	0.000000	FIXED	-0.264854	**-1.98**
G_sexM999	-0.264133	-1.72	-0.563628	**-3.97**	-0.555001	**-3.41**	-0.030834	-0.14
G_edNG1	-0.091624	**-2.13**	-0.091409	**-2.39**	-0.115609	**-2.90**	-0.269677	-1.53
G_edNG3	0.000000	FIXED	0.000000	0.00	0.000000	FIXED	0.285189	1.84
G_edNG4	0.075006	**2.22**	0.023052	0.93	0.078109	**2.31**	0.218497	1.29
G_edNG5	-0.104742	-1.70	-0.097916	-1.48	0.000000	FIXED	-0.488620	-1.29
G_edNG7	0.074408	**2.16**	-0.044297	-1.21	0.000000	FIXED	0.187927	1.11
G_edNG9	-0.111716	**-2.47**	0.000000	0.00	-0.118721	**-2.98**	-0.745136	**-3.46**
G_edNG999	-0.348265	-1.63	0.022434	0.11	0.222336	1.15	0.783191	**2.54**
G_edS1	0.000000	FIXED	0.000000	0.00	0.000000	FIXED	-0.308305	**-3.00**
G_edS3	-0.096816	**-2.53**	0.000000	0.00	0.000000	FIXED	0.000000	FIXED
G_edS4	-0.067197	-1.86	-0.095386	**-2.57**	-0.064835	-1.69	0.000000	FIXED
G_edS5	0.000000	FIXED	0.000000	0.00	0.076672	1.47	0.128582	0.77
G_edS7			-0.067159	-1.90	0.000000	FIXED	0.000000	FIXED
G_edS999	0.561830	**3.25**	0.755945	**4.55**	0.465075	**2.64**	-0.297631	-1.24
G_edGC1	0.000000	FIXED	0.000000	0.00	0.000000	FIXED	0.229713	1.82
G_edGC3	0.000000	FIXED	0.000000	0.00	0.000000	FIXED	-0.119111	-0.74
G_edGC4	-0.035313	-0.94	-0.076160	**-1.99**	0.000000	FIXED	-0.479138	**-2.15**
G_edGC5	0.000000	FIXED	-0.056052	-0.96	0.000000	FIXED	-0.500291	-1.32
G_edGC6	0.000000	FIXED	0.000000	0.00	-0.119665	**-2.56**	-0.318908	**-2.00**
G_edGC7	0.060868	1.71	0.012656	0.40				
G_edGC999	0.674998	**3.50**	0.178732	0.89	0.079015	0.34	0.452194	1.42
G_AQA2	0.000000	FIXED	0.000000	0.00	0.131126	**3.90**	0.000000	FIXED
G_AQA3	-0.095033	**-2.13**	-0.071556	**-2.48**	-0.060232	-1.53	-0.453822	**-3.05**
G_AQA4	0.000000	FIXED	-0.037582	-1.70	0.000000	FIXED	0.000000	FIXED
G_AQA5	-0.120818	**-2.27**	-0.078144	-1.73	0.000000	FIXED	0.000000	FIXED
G_AQA6	0.000000	FIXED	0.000000	0.00	-0.063617	**-2.11**	0.000000	FIXED
G_AQA9	0.065356	**2.17**	0.000000	0.00	0.060464	1.71	0.000000	FIXED
G_AQA999	0.014532	0.07	0.518593	**2.41**	0.181568	0.77	-0.092820	-0.29
G_RS999	0.088162	0.67	-0.044285	-0.34	-0.096464	-0.66	0.043263	0.22
G_AFQT999	-0.002293	-0.43	-0.004953	-0.94	0.003845	0.61	0.035553	**3.58**
LAMBDA	8.859739	1.82	9.605288	1.72	7.358447	1.03	2.919374	0.33
DELTA	0.831793	-1.50	0.857459	-1.42	0.753447	**-3.04**	0.535445	**-7.50**

APPENDIX C: MODEL FIT DIAGNOSTICS

Table C.1. Fit Diagnostics for First Quarter Model

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
ALL	CL	3181	0.1374	0.1354	-0.0020	1.0145
	CO	2656	0.3691	0.3698	0.0007	0.9980
	EL	2517	0.1210	0.1211	0.0000	0.9998
	FA	2584	0.0974	0.0989	0.0014	0.9857
	GM	2051	0.0414	0.0427	0.0013	0.9699
	MM	3125	0.1311	0.1310	-0.0001	1.0007
	OF	2964	0.0683	0.0682	-0.0001	1.0008
	SC	136	0.2533	0.2308	-0.0225	1.0974
	ST	2942	0.2218	0.2220	0.0002	0.9993
	Non-Acc	4080	0.1687	0.1688	0.0002	0.9990
Multp-Opp	CL	3119	0.1245	0.1231	-0.0014	1.0117
	CO	2537	0.3412	0.3409	-0.0003	1.0009
	EL	2493	0.1149	0.1150	0.0001	0.9991
	FA	2563	0.0914	0.0924	0.0010	0.9894
	GM	2031	0.0352	0.0366	0.0014	0.9608
	MM	3086	0.1236	0.1234	-0.0002	1.0017
	OF	2946	0.0643	0.0639	-0.0004	1.0067
	SC	131	0.2333	0.2177	-0.0156	1.0716
	ST	2860	0.2044	0.2045	0.0001	0.9995
	Non-Acc	3690	0.1702	0.1711	0.0009	0.9950
Single-Opp	CL	62	0.8230	0.7928	-0.0302	1.0381
	CO	119	0.8730	0.8928	0.0198	0.9779
	EL	24	0.8465	0.8376	-0.0089	1.0107
	FA	21	0.8607	0.9167	0.0560	0.9389
	GM	20	0.8033	0.7859	-0.0173	1.0221
	MM	39	0.8327	0.8431	0.0104	0.9877
	OF	18	0.8198	0.8900	0.0702	0.9211
	SC	5	0.8226	0.6038	-0.2188	1.3624
	ST	82	0.8300	0.8323	0.0023	0.9973
	Non-Acc	390	0.1542	0.1480	-0.0062	1.0421
Male	CL	2545	0.1051	0.0974	-0.0077	1.0794
	CO	2463	0.3947	0.3953	0.0006	0.9985
	EL	2048	0.1205	0.1195	-0.0009	1.0076
	FA	2497	0.1001	0.1018	0.0017	0.9836
	GM	1526	0.0406	0.0426	0.0020	0.9537
	MM	2541	0.1369	0.1367	-0.0002	1.0014
	OF	2409	0.0616	0.0625	0.0009	0.9853
	SC	110	0.2301	0.2283	-0.0018	1.0077
	ST	2318	0.1715	0.1759	0.0044	0.9751
	Non-Acc	3259	0.1570	0.1573	0.0003	0.9980
Female	CL	636	0.2733	0.2956	0.0223	0.9246
	CO	193	0.0138	0.0167	0.0029	0.8271
	EL	469	0.1237	0.1281	0.0044	0.9654
	FA	87	0.0116	0.0050	-0.0066	2.3098
	GM	525	0.0437	0.0428	-0.0009	1.0200
	MM	584	0.1043	0.1047	0.0003	0.9968
	OF	555	0.0991	0.0946	-0.0045	1.0481
	SC	26	0.3449	0.2407	-0.1042	1.4328
	ST	624	0.4215	0.4050	-0.0165	1.0408
	Non-Acc	821	0.2175	0.2170	-0.0004	1.0021

Table C.1. Fit Diagnostics for First Quarter Model (continued)

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
HSGC	CL	418	0.1115	0.1066	-0.0050	1.0465
	CO	364	0.2955	0.3071	0.0116	0.9621
	EL	365	0.1247	0.1016	-0.0231	1.2275
	FA	332	0.0572	0.0578	0.0007	0.9887
	GM	290	0.0233	0.0286	0.0053	0.8145
	MM	417	0.0914	0.0815	-0.0099	1.1212
	OF	399	0.0637	0.0654	0.0017	0.9736
	SC	15	0.2355	0.1714	-0.0641	1.3741
	ST	433	0.2609	0.2783	0.0174	0.9374
	Non-Acc	533	0.2272	0.2298	0.0025	0.9890
HSG	CL	1775	0.1466	0.1514	0.0048	0.9680
	CO	1436	0.3887	0.3854	-0.0033	1.0086
	EL	1301	0.1229	0.1277	0.0049	0.9619
	FA	1384	0.0959	0.0980	0.0021	0.9787
	GM	1129	0.0435	0.0438	0.0003	0.9935
	MM	1725	0.1306	0.1312	0.0005	0.9959
	OF	1624	0.0610	0.0607	-0.0003	1.0052
	SC	37	0.3049	0.3145	0.0097	0.9693
	ST	1537	0.2232	0.2152	-0.0080	1.0372
	Non-Acc	2187	0.1510	0.1503	-0.0007	1.0049
Senior	CL	592	0.1539	0.1277	-0.0262	1.2053
	CO	468	0.3107	0.3160	0.0053	0.9832
	EL	497	0.0949	0.0929	-0.0020	1.0213
	FA	490	0.0619	0.0621	0.0002	0.9970
	GM	337	0.0502	0.0512	0.0010	0.9803
	MM	543	0.0951	0.1020	0.0069	0.9324
	OF	546	0.0541	0.0549	0.0007	0.9867
	SC	55	0.3083	0.3060	-0.0022	1.0073
	ST	577	0.2378	0.2529	0.0151	0.9404
	Non-Acc	733	0.2207	0.2215	0.0008	0.9962
NG	CL	396	0.0966	0.1046	0.0080	0.9237
	CO	388	0.4382	0.4380	-0.0002	1.0004
	EL	354	0.1487	0.1583	0.0096	0.9393
	FA	378	0.1884	0.1897	0.0012	0.9935
	GM	295	0.0408	0.0423	0.0015	0.9648
	MM	440	0.2193	0.2173	-0.0020	1.0094
	OF	395	0.1254	0.1234	-0.0020	1.0162
	SC	29	0.0990	0.0237	-0.0753	4.1852
	ST	395	0.1462	0.1364	-0.0098	1.0717
	Non-Acc	627	0.1174	0.1180	0.0006	0.9953

Table C.1. Fit Diagnostics for First Quarter Model (continued)

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
Cat1-3A	CL	2434	0.1070	0.1048	-0.0021	1.0204
	CO	2148	0.3512	0.3605	0.0093	0.9741
	EL	2256	0.1207	0.1213	0.0006	0.9952
	FA	2089	0.0953	0.0945	-0.0008	1.0087
	GM	1709	0.0283	0.0284	0.0002	0.9942
	MM	2491	0.1194	0.1159	-0.0036	1.0308
	OF	2359	0.0592	0.0553	-0.0039	1.0702
	SC	83	0.2376	0.3312	0.0936	0.7174
	ST	2466	0.2282	0.2259	-0.0022	1.0099
	Non-Acc	3079	0.1618	0.1621	0.0004	0.9977
Cat3B	CL	747	0.2357	0.2343	-0.0014	1.0060
	CO	508	0.4426	0.4079	-0.0347	1.0850
	EL	261	0.1234	0.1187	-0.0047	1.0397
	FA	495	0.1066	0.1175	0.0109	0.9071
	GM	342	0.1080	0.1150	0.0070	0.9392
	MM	634	0.1769	0.1904	0.0135	0.9289
	OF	605	0.1030	0.1176	0.0146	0.8762
	SC	53	0.2751	0.0918	-0.1833	2.9975
	ST	476	0.1901	0.2022	0.0122	0.9399
	Non-Acc	1001	0.1896	0.1891	-0.0005	1.0025

Table C.2. Fit Diagnostics for Second Quarter Model

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
ALL	CL	3419	0.1673	0.1657	-0.0017	1.0100
	CO	3069	0.3650	0.3633	-0.0017	1.0048
	EL	2826	0.1279	0.1289	0.0010	0.9923
	FA	2631	0.1078	0.1067	-0.0010	1.0097
	GM	1723	0.0324	0.0351	0.0027	0.9225
	MM	3226	0.1303	0.1324	0.0021	0.9840
	OF	3040	0.0550	0.0552	0.0002	0.9960
	SC	229	0.1683	0.1664	-0.0019	1.0116
	ST	3251	0.2156	0.2154	-0.0002	1.0012
	Non-Acc	4389	0.1471	0.1472	0.0001	0.9995
Mult-Opp	CL	3343	0.1528	0.1502	-0.0025	1.0169
	CO	2901	0.3328	0.3323	-0.0006	1.0018
	EL	2800	0.1225	0.1225	0.0000	1.0000
	FA	2602	0.0999	0.0994	-0.0006	1.0055
	GM	1704	0.0279	0.0306	0.0027	0.9133
	MM	3187	0.1228	0.1240	0.0012	0.9906
	OF	3015	0.0497	0.0494	-0.0003	1.0067
	SC	224	0.1525	0.1551	0.0026	0.9832
	ST	3157	0.1959	0.1956	-0.0003	1.0017
	Non-Acc	3908	0.1483	0.1496	0.0013	0.9913
Single-Opp	CL	76	0.8485	0.8880	0.0394	0.9556
	CO	168	0.8798	0.8596	-0.0202	1.0235
	EL	26	0.8653	1.0000	0.1347	0.8653
	FA	29	0.8686	0.8199	-0.0487	1.0594
	GM	19	0.8156	0.8311	0.0155	0.9813
	MM	39	0.8553	0.9505	0.0953	0.8998
	OF	25	0.8384	0.9207	0.0823	0.9106
	SC	5	0.8700	0.6672	-0.2028	1.3040
	ST	94	0.8496	0.8522	0.0027	0.9969
	Non-Acc	481	0.1375	0.1273	-0.0102	1.0803
Male	CL	2701	0.1263	0.1188	-0.0074	1.0627
	CO	2800	0.3981	0.3965	-0.0016	1.0041
	EL	2273	0.1268	0.1278	0.0010	0.9919
	FA	2562	0.1097	0.1083	-0.0014	1.0131
	GM	1213	0.0374	0.0398	0.0024	0.9389
	MM	2597	0.1433	0.1450	0.0017	0.9884
	OF	2416	0.0450	0.0451	0.0000	0.9990
	SC	131	0.1568	0.1966	0.0398	0.7977
	ST	2563	0.1686	0.1744	0.0058	0.9670
	Non-Acc	3475	0.1298	0.1295	-0.0002	1.0019
Female	CL	718	0.3193	0.3391	0.0197	0.9418
	CO	269	0.0149	0.0120	-0.0028	1.2346
	EL	553	0.1327	0.1335	0.0008	0.9937
	FA	69	0.0282	0.0426	0.0143	0.6634
	GM	510	0.0202	0.0236	0.0034	0.8548
	MM	629	0.0760	0.0800	0.0040	0.9504
	OF	624	0.0927	0.0936	0.0009	0.9905
	SC	98	0.1829	0.1280	-0.0549	1.4293
	ST	688	0.3908	0.3681	-0.0226	1.0615
	Non-Acc	914	0.2134	0.2147	0.0013	0.9940

Table C.2. Fit Diagnostics for Second Quarter Model (continued)

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
HSGC	CL	429	0.1640	0.1729	0.0089	0.9486
	CO	376	0.3280	0.3116	-0.0164	1.0528
	EL	384	0.1406	0.1525	0.0119	0.9220
	FA	335	0.0681	0.0620	-0.0061	1.0987
	GM	244	0.0191	0.0208	0.0017	0.9181
	MM	421	0.1059	0.0986	-0.0074	1.0747
	OF	406	0.0577	0.0577	0.0000	0.9997
	SC	24	0.3087	0.2744	-0.0343	1.1249
	ST	469	0.2827	0.2915	0.0089	0.9696
	Non-Acc	567	0.1468	0.1455	-0.0013	1.0089
HSG	CL	1964	0.1713	0.1767	0.0054	0.9692
	CO	1751	0.3613	0.3586	-0.0027	1.0076
	EL	1521	0.1167	0.1162	-0.0006	1.0048
	FA	1514	0.1154	0.1159	0.0005	0.9957
	GM	993	0.0331	0.0380	0.0050	0.8697
	MM	1813	0.1311	0.1335	0.0024	0.9818
	OF	1681	0.0593	0.0597	0.0005	0.9921
	SC	91	0.1676	0.1448	-0.0227	1.1571
	ST	1799	0.2025	0.1950	-0.0076	1.0388
	Non-Acc	2378	0.1229	0.1228	-0.0001	1.0006
Senior	CL	656	0.1856	0.1540	-0.0316	1.2055
	CO	568	0.3300	0.3445	0.0145	0.9580
	EL	572	0.1310	0.1097	-0.0213	1.1939
	FA	473	0.0515	0.0529	0.0013	0.9749
	GM	284	0.0489	0.0457	-0.0032	1.0705
	MM	623	0.1075	0.1220	0.0145	0.8812
	OF	613	0.0397	0.0376	-0.0021	1.0562
	SC	92	0.1367	0.1756	0.0389	0.7785
	ST	635	0.2070	0.2274	0.0205	0.9100
	Non-Acc	852	0.2221	0.2232	0.0010	0.9953
NG	CL	370	0.1154	0.1202	0.0048	0.9600
	CO	374	0.4708	0.4623	-0.0085	1.0184
	EL	349	0.1595	0.1961	0.0367	0.8131
	FA	309	0.2011	0.1942	-0.0069	1.0353
	GM	202	0.0204	0.0221	0.0017	0.9229
	MM	369	0.1957	0.1841	-0.0116	1.0632
	OF	340	0.0597	0.0634	0.0037	0.9413
	SC	22	0.1686	0.1057	-0.0629	1.5949
	ST	348	0.2136	0.1994	-0.0142	1.0713
	Non-Acc	592	0.1314	0.1318	0.0005	0.9964

Table C.2. Fit Diagnostics for Second Quarter Model (continued)

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
Cat1-3A	CL	2408	0.1304	0.1186	-0.0118	1.0998
	CO	2270	0.3320	0.3384	0.0064	0.9812
	EL	2351	0.1332	0.1340	0.0009	0.9935
	FA	2048	0.1002	0.0986	-0.0016	1.0164
	GM	1342	0.0216	0.0241	0.0025	0.8963
	MM	2473	0.1195	0.1165	-0.0030	1.0260
	OF	2324	0.0445	0.0461	0.0016	0.9652
	SC	143	0.1861	0.2023	0.0162	0.9201
	ST	2554	0.2202	0.2248	0.0046	0.9794
	Non-Acc	3110	0.1549	0.1553	0.0005	0.9970
Cat3B	CL	974	0.2517	0.2740	0.0223	0.9186
	CO	769	0.4545	0.4209	-0.0336	1.0799
	EL	468	0.1026	0.1051	0.0025	0.9764
	FA	577	0.1338	0.1355	0.0017	0.9873
	GM	362	0.0681	0.0730	0.0049	0.9330
	MM	729	0.1619	0.1816	0.0198	0.8912
	OF	684	0.0844	0.0833	-0.0011	1.0136
	SC	84	0.1357	0.1043	-0.0314	1.3016
	ST	692	0.2001	0.1830	-0.0171	1.0934
	Non-Acc	1230	0.1291	0.1303	0.0011	0.9912
Cat4	CL	37	0.2943	0.3072	0.0129	0.9581
	CO	30	0.5390	0.7608	0.2218	0.7085
	EL	7	0.0562	0.0000	-0.0562	.
	FA	6	0.1607	0.0810	-0.0796	1.9832
	GM	19	0.1212	0.0960	-0.0252	1.2622
	MM	24	0.2800	0.2737	-0.0063	1.0231
	OF	32	0.1750	0.1014	-0.0736	1.7263
	SC	2	0.1615	0.0000	-0.1615	.
	ST	5	0.0953	0.0000	-0.0953	.
	Non-Acc	49	0.1195	0.0665	-0.0530	1.7979

Table C.3. Fit Diagnostics for Third Quarter Model

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
ALL	CL	3400	0.1967	0.1945	-0.0023	1.0116
	CO	2511	0.3321	0.3322	0.0001	0.9998
	EL	2493	0.1423	0.1430	0.0007	0.9952
	FA	2561	0.1260	0.1249	-0.0012	1.0093
	GM	1759	0.0349	0.0331	-0.0018	1.0539
	MM	3213	0.1607	0.1632	0.0025	0.9846
	OF	3200	0.0936	0.0941	0.0005	0.9947
	SC	170	0.1512	0.1488	-0.0024	1.0163
	ST	2898	0.2256	0.2268	0.0013	0.9944
	Non-Acc	4394	0.1541	0.1539	-0.0002	1.0015
Mult-Opp	CL	3324	0.1811	0.1786	-0.0026	1.0143
	CO	2380	0.3057	0.3050	-0.0007	1.0023
	EL	2471	0.1367	0.1370	0.0003	0.9977
	FA	2541	0.1191	0.1199	0.0009	0.9929
	GM	1743	0.0310	0.0295	-0.0015	1.0510
	MM	3178	0.1535	0.1555	0.0020	0.9874
	OF	3168	0.0856	0.0862	0.0006	0.9928
	SC	166	0.1404	0.1359	-0.0044	1.0327
	ST	2808	0.2055	0.2070	0.0015	0.9927
	Non-Acc	3968	0.1565	0.1560	-0.0005	1.0030
Single-Opp	CL	76	0.8603	0.8711	0.0108	0.9876
	CO	131	0.8918	0.9084	0.0166	0.9817
	EL	22	0.8630	0.9113	0.0483	0.9470
	FA	20	0.8627	0.6484	-0.2143	1.3305
	GM	16	0.8543	0.7936	-0.0607	1.0765
	MM	35	0.8418	0.8984	0.0566	0.9370
	OF	32	0.8593	0.8473	-0.0120	1.0141
	SC	4	0.8693	1.0000	0.1307	0.8693
	ST	90	0.8711	0.8641	-0.0070	1.0081
	Non-Acc	426	0.1300	0.1321	0.0022	0.9835
Male	CL	2772	0.1613	0.1590	-0.0023	1.0146
	CO	2441	0.3407	0.3411	0.0004	0.9988
	EL	1939	0.1381	0.1368	-0.0013	1.0098
	FA	2527	0.1273	0.1263	-0.0010	1.0076
	GM	1278	0.0408	0.0378	-0.0031	1.0809
	MM	2606	0.1684	0.1705	0.0021	0.9874
	OF	2660	0.0864	0.0907	0.0044	0.9520
	SC	119	0.1042	0.1350	0.0308	0.7722
	ST	2318	0.1923	0.1902	-0.0021	1.0112
	Non-Acc	3521	0.1377	0.1373	-0.0004	1.0026
Female	CL	628	0.3498	0.3478	-0.0020	1.0057
	CO	70	0.0299	0.0175	-0.0124	1.7089
	EL	554	0.1567	0.1644	0.0077	0.9533
	FA	34	0.0182	0.0000	-0.0182	.
	GM	481	0.0190	0.0206	0.0016	0.9209
	MM	607	0.1272	0.1314	0.0042	0.9683
	OF	540	0.1284	0.1103	-0.0181	1.1644
	SC	51	0.2618	0.1812	-0.0806	1.4447
	ST	580	0.3573	0.3720	0.0147	0.9604
	Non-Acc	873	0.2194	0.2196	0.0003	0.9987

Table C.3. Fit Diagnostics for Third Quarter Model (continued)

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
HSGC	CL	434	0.2033	0.1984	-0.0050	1.0250
	CO	287	0.3156	0.2769	-0.0387	1.1396
	EL	317	0.1580	0.1569	-0.0011	1.0069
	FA	297	0.0942	0.1097	0.0154	0.8592
	GM	253	0.0245	0.0220	-0.0025	1.1122
	MM	403	0.0821	0.0821	-0.0001	1.0008
	OF	391	0.0722	0.0622	-0.0100	1.1606
	SC	13	0.1631	0.3186	0.1554	0.5121
	ST	409	0.3152	0.3431	0.0279	0.9186
	Non-Acc	538	0.1506	0.1518	0.0012	0.9922
HSG	CL	1665	0.2198	0.2198	0.0000	1.0000
	CO	1162	0.3069	0.3285	0.0217	0.9341
	EL	1149	0.1410	0.1395	-0.0015	1.0107
	FA	1241	0.1204	0.1157	-0.0046	1.0401
	GM	837	0.0313	0.0337	0.0023	0.9312
	MM	1532	0.1677	0.1702	0.0025	0.9853
	OF	1551	0.0965	0.0991	0.0026	0.9735
	SC	102	0.1602	0.1345	-0.0258	1.1917
	ST	1326	0.2332	0.2143	-0.0190	1.0884
	Non-Acc	2064	0.1366	0.1370	0.0004	0.9974
Senior	CL	747	0.1822	0.1687	-0.0135	1.0798
	CO	651	0.3785	0.3581	-0.0203	1.0568
	EL	618	0.1319	0.1543	0.0224	0.8546
	FA	553	0.0738	0.0731	-0.0007	1.0092
	GM	383	0.0427	0.0363	-0.0064	1.1755
	MM	707	0.1210	0.1148	-0.0063	1.0546
	OF	691	0.0683	0.0629	-0.0054	1.0856
	SC	22	0.1431	0.2525	0.1095	0.5665
	ST	680	0.2117	0.2384	0.0267	0.8880
	Non-Acc	981	0.1865	0.1866	0.0001	0.9993
NG	CL	554	0.1425	0.1506	0.0080	0.9467
	CO	411	0.3399	0.3396	-0.0002	1.0007
	EL	409	0.1497	0.1260	-0.0237	1.1878
	FA	470	0.2192	0.2164	-0.0028	1.0130
	GM	286	0.0441	0.0372	-0.0069	1.1853
	MM	571	0.2440	0.2591	0.0150	0.9419
	OF	567	0.1295	0.1381	0.0086	0.9376
	SC	33	0.1256	0.0642	-0.0615	1.9575
	ST	483	0.1520	0.1510	-0.0010	1.0068
	Non-Acc	811	0.1615	0.1585	-0.0030	1.0189

Table C.3. Fit Diagnostics for Third Quarter Model (continued)

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
Cat1-3A	CL	2354	0.1538	0.1543	0.0005	0.9964
	CO	1720	0.3156	0.3130	-0.0027	1.0085
	EL	2042	0.1453	0.1454	0.0001	0.9992
	FA	1952	0.1088	0.1084	-0.0004	1.0040
	GM	1394	0.0282	0.0274	-0.0007	1.0273
	MM	2462	0.1334	0.1345	0.0011	0.9916
	OF	2364	0.0801	0.0769	-0.0032	1.0417
	SC	88	0.1896	0.2234	0.0338	0.8488
	ST	2336	0.2406	0.2443	0.0037	0.9848
	Non-Acc	3017	0.1544	0.1539	-0.0005	1.0035
Cat3B	CL	977	0.2902	0.2795	-0.0107	1.0382
	CO	722	0.3599	0.3587	-0.0012	1.0032
	EL	427	0.1308	0.1363	0.0055	0.9598
	FA	579	0.1814	0.1782	-0.0032	1.0181
	GM	326	0.0580	0.0559	-0.0021	1.0381
	MM	692	0.2336	0.2550	0.0214	0.9162
	OF	771	0.1289	0.1387	0.0098	0.9293
	SC	80	0.1125	0.0722	-0.0404	1.5592
	ST	544	0.1654	0.1541	-0.0112	1.0728
	Non-Acc	1269	0.1552	0.1538	-0.0014	1.0091
Cat4	CL	69	0.2536	0.2808	0.0272	0.9031
	CO	69	0.4591	0.5438	0.0847	0.8443
	EL	24	0.0931	0.0514	-0.0417	1.8099
	FA	30	0.1301	0.1235	-0.0066	1.0536
	GM	39	0.0914	0.0537	-0.0377	1.7027
	MM	59	0.4046	0.2404	-0.1642	1.6831
	OF	65	0.1472	0.1664	0.0192	0.8846
	SC	2	0.0455	0.0000	-0.0455	.
	ST	18	0.1776	0.2485	0.0709	0.7145
	Non-Acc	108	0.1320	0.1541	0.0221	0.8564

Table C.4. Fit Diagnostics for Fourth Quarter Model

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
ALL	CL	3183	0.1882	0.1917	0.0035	0.9817
	CO	2962	0.3377	0.3375	-0.0001	1.0004
	EL	2670	0.1221	0.1220	-0.0001	1.0005
	FA	2612	0.0952	0.0935	-0.0018	1.0187
	GM	2474	0.0313	0.0313	0.0000	1.0007
	MM	3258	0.1472	0.1465	-0.0007	1.0047
	OF	3110	0.0773	0.0776	0.0003	0.9967
	SC	475	0.1835	0.1808	-0.0026	1.0146
	ST	3253	0.2526	0.2509	-0.0017	1.0069
	Non-Acc	4420	0.1249	0.1254	0.0006	0.9956
Mult-Opp	CL	3128	0.1761	0.1784	0.0023	0.9869
	CO	2835	0.3118	0.3118	0.0000	0.9998
	EL	2645	0.1152	0.1153	0.0001	0.9993
	FA	2597	0.0912	0.0893	-0.0019	1.0214
	GM	2462	0.0290	0.0288	-0.0002	1.0063
	MM	3225	0.1408	0.1397	-0.0011	1.0081
	OF	3086	0.0716	0.0712	-0.0004	1.0055
	SC	470	0.1747	0.1715	-0.0032	1.0189
	ST	3168	0.2325	0.2324	-0.0001	1.0005
	Non-Acc	4039	0.1262	0.1273	0.0011	0.9913
Single-Opp	CL	55	0.8799	0.9496	0.0697	0.9266
	CO	127	0.9365	0.9318	-0.0047	1.0050
	EL	25	0.8481	0.8326	-0.0155	1.0186
	FA	15	0.7886	0.8141	0.0256	0.9686
	GM	12	0.7692	0.8198	0.0506	0.9383
	MM	33	0.8168	0.8625	0.0457	0.9470
	OF	24	0.8043	0.8863	0.0820	0.9075
	SC	5	0.9494	1.0000	0.0506	0.9494
	ST	85	0.9117	0.8571	-0.0546	1.0637
	Non-Acc	381	0.1107	0.1054	-0.0052	1.0497
Male	CL	2515	0.1360	0.1330	-0.0030	1.0228
	CO	2731	0.3649	0.3647	-0.0002	1.0005
	EL	2118	0.1245	0.1245	0.0000	1.0002
	FA	2509	0.0987	0.0969	-0.0018	1.0186
	GM	1894	0.0300	0.0302	0.0003	0.9902
	MM	2640	0.1594	0.1589	-0.0005	1.0031
	OF	2486	0.0608	0.0616	0.0008	0.9870
	SC	269	0.1505	0.1900	0.0395	0.7922
	ST	2523	0.2040	0.2038	-0.0002	1.0010
	Non-Acc	3425	0.1154	0.1157	0.0003	0.9970
Female	CL	668	0.3799	0.4074	0.0275	0.9326
	CO	231	0.0252	0.0255	0.0003	0.9865
	EL	552	0.1128	0.1126	-0.0002	1.0019
	FA	103	0.0095	0.0089	-0.0006	1.0638
	GM	580	0.0357	0.0346	-0.0010	1.0301
	MM	618	0.0957	0.0941	-0.0016	1.0166
	OF	624	0.1413	0.1394	-0.0019	1.0134
	SC	206	0.2265	0.1689	-0.0576	1.3410
	ST	730	0.4147	0.4078	-0.0069	1.0169
	Non-Acc	995	0.1567	0.1580	0.0013	0.9920

Table C.4. Fit Diagnostics for Fourth Quarter Model (continued)

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
HSGC	CL	334	0.2078	0.2008	-0.0070	1.0349
	CO	304	0.2969	0.2594	-0.0375	1.1444
	EL	277	0.0932	0.0949	0.0017	0.9822
	FA	278	0.0508	0.0485	-0.0022	1.0456
	GM	262	0.0126	0.0127	0.0001	0.9915
	MM	340	0.0829	0.0839	0.0010	0.9878
	OF	319	0.0607	0.0565	-0.0042	1.0739
	SC	41	0.2420	0.3139	0.0720	0.7708
	ST	378	0.3335	0.3656	0.0321	0.9122
	Non-Acc	462	0.1559	0.1545	-0.0013	1.0085
HSG	CL	1660	0.2046	0.2145	0.0099	0.9538
	CO	1507	0.3254	0.3093	-0.0161	1.0521
	EL	1280	0.1109	0.1242	0.0133	0.8929
	FA	1395	0.1001	0.1019	0.0018	0.9826
	GM	1364	0.0360	0.0363	0.0002	0.9936
	MM	1669	0.1470	0.1473	0.0003	0.9981
	OF	1574	0.0802	0.0842	0.0040	0.9524
	SC	226	0.1998	0.1483	-0.0515	1.3470
	ST	1682	0.2612	0.2548	-0.0064	1.0250
	Non-Acc	2286	0.1210	0.1225	0.0015	0.9877
Senior	CL	946	0.1696	0.1667	-0.0029	1.0175
	CO	893	0.3728	0.4171	0.0444	0.8937
	EL	864	0.1307	0.1099	-0.0208	1.1888
	FA	713	0.0789	0.0679	-0.0110	1.1616
	GM	649	0.0319	0.0316	-0.0003	1.0096
	MM	970	0.1581	0.1531	-0.0050	1.0325
	OF	965	0.0700	0.0644	-0.0056	1.0864
	SC	175	0.1530	0.1940	0.0411	0.7883
	ST	924	0.2416	0.2324	-0.0093	1.0398
	Non-Acc	1277	0.1012	0.1019	0.0007	0.9933
NG	CL	243	0.1222	0.1211	-0.0010	1.0086
	CO	258	0.3409	0.3297	-0.0111	1.0337
	EL	249	0.1819	0.1810	-0.0009	1.0048
	FA	226	0.1692	0.1743	0.0051	0.9706
	GM	199	0.0228	0.0217	-0.0010	1.0468
	MM	279	0.1893	0.1951	0.0058	0.9703
	OF	252	0.1078	0.1120	0.0042	0.9625
	SC	33	0.1569	0.1491	-0.0079	1.0528
	ST	269	0.1245	0.1288	0.0043	0.9665
	Non-Acc	395	0.1841	0.1810	-0.0031	1.0169

Table C.4. Fit Diagnostics for Fourth Quarter Model (continued)

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
Cat1-3A	CL	2319	0.1419	0.1465	0.0046	0.9687
	CO	2151	0.3059	0.3219	0.0160	0.9503
	EL	2205	0.1206	0.1201	-0.0004	1.0036
	FA	2055	0.0924	0.0867	-0.0057	1.0659
	GM	1921	0.0255	0.0235	-0.0021	1.0875
	MM	2534	0.1328	0.1243	-0.0085	1.0684
	OF	2314	0.0623	0.0577	-0.0046	1.0795
	SC	294	0.2267	0.2416	0.0149	0.9385
	ST	2633	0.2701	0.2686	-0.0015	1.0057
	Non-Acc	3133	0.1236	0.1247	0.0010	0.9916
Cat3B	CL	859	0.3121	0.3123	0.0001	0.9995
	CO	809	0.4226	0.3779	-0.0447	1.1182
	EL	465	0.1293	0.1310	0.0018	0.9865
	FA	556	0.1060	0.1195	0.0136	0.8865
	GM	552	0.0521	0.0598	0.0077	0.8705
	MM	722	0.2003	0.2283	0.0279	0.8777
	OF	795	0.1211	0.1356	0.0145	0.8929
	SC	180	0.1096	0.0777	-0.0319	1.4104
	ST	619	0.1774	0.1748	-0.0026	1.0146
	Non-Acc	1281	0.1281	0.1279	-0.0002	1.0016
Cat4	CL	5	0.6333	0.7044	0.0711	0.8991
	CO	2	0.6361	1.0000	0.3639	0.6361
	EL	0	.	.	.	.
	FA	1	0.0725	0.0000	-0.0725	.
	GM	1	0.1852	0.0000	-0.1852	.
	MM	2	0.1425	0.2086	0.0661	0.6830
	OF	1	0.3143	0.0000	-0.3143	.
	SC	1	0.1244	0.0000	-0.1244	.
	ST	1	0.0716	0.0000	-0.0716	.
	Non-Acc	6	0.0994	0.0000	-0.0994	.

APPENDIX D: OUT-OF-SAMPLE MODEL DIAGNOSTICS

Table D.1. Out-of-Sample Fit Diagnostics for First Quarter Model

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
ALL	CL	6609	0.1606	0.1595	-0.0011	1.0066
	CO	6448	0.4323	0.4050	-0.0273	1.0673
	EL	5082	0.1366	0.1477	0.0110	0.9253
	FA	5396	0.1161	0.1204	0.0043	0.9642
	GM	4102	0.0574	0.0509	-0.0066	1.1293
	MM	6346	0.1485	0.1570	0.0084	0.9462
	OF	6078	0.0798	0.0825	0.0027	0.9670
	SC	282	0.3060	0.2514	-0.0546	1.2172
	ST	6318	0.2618	0.2552	-0.0066	1.0260
	Non-Acc	10153	0.1662	0.1774	0.0112	0.9369
Multiple-Opp	CL	6235	0.1172	0.1155	-0.0017	1.0147
	CO	5272	0.3399	0.3066	-0.0333	1.1086
	EL	4969	0.1190	0.1297	0.0107	0.9177
	FA	5250	0.0939	0.0974	0.0035	0.9644
	GM	4003	0.0365	0.0305	-0.0060	1.1976
	MM	6197	0.1275	0.1345	0.0071	0.9476
	OF	5981	0.0661	0.0691	0.0030	0.9566
	SC	264	0.2460	0.1973	-0.0487	1.2470
	ST	5755	0.2035	0.1957	-0.0078	1.0396
	Non-Acc	7418	0.1701	0.1881	0.0180	0.9044
Single-Opp	CL	374	0.8195	0.8284	0.0089	0.9893
	CO	1176	0.8681	0.8693	0.0012	0.9986
	EL	113	0.8602	0.8864	0.0262	0.9705
	FA	146	0.8577	0.8900	0.0324	0.9636
	GM	99	0.7990	0.7728	-0.0262	1.0338
	MM	149	0.8196	0.8722	0.0526	0.9397
	OF	97	0.8185	0.8063	-0.0122	1.0151
	SC	18	0.8613	0.7523	-0.1091	1.1450
	ST	563	0.8298	0.8341	0.0043	0.9948
	Non-Acc	2735	0.1559	0.1493	-0.0066	1.0440
Male	CL	5295	0.1242	0.1187	-0.0055	1.0466
	CO	6060	0.4577	0.4291	-0.0286	1.0667
	EL	4169	0.1405	0.1543	0.0138	0.9108
	FA	5211	0.1197	0.1245	0.0048	0.9612
	GM	3056	0.0588	0.0503	-0.0085	1.1698
	MM	5226	0.1562	0.1694	0.0132	0.9222
	OF	5007	0.0719	0.0769	0.0051	0.9340
	SC	216	0.3075	0.2898	-0.0177	1.0609
	ST	4958	0.2050	0.2066	0.0017	0.9920
	Non-Acc	8272	0.1550	0.1603	0.0053	0.9669
Female	CL	1314	0.3070	0.3240	0.0170	0.9476
	CO	388	0.0405	0.0342	-0.0064	1.1869
	EL	913	0.1188	0.1174	-0.0014	1.0120
	FA	185	0.0110	0.0000	-0.0110	.
	GM	1046	0.0535	0.0527	-0.0008	1.0156
	MM	1120	0.1125	0.0986	-0.0139	1.1404
	OF	1071	0.1167	0.1085	-0.0082	1.0757
	SC	66	0.3009	0.1155	-0.1854	2.6058
	ST	1360	0.4709	0.4337	-0.0371	1.0856
	Non-Acc	1881	0.2152	0.2521	0.0369	0.8535

Table D.1. Out-of-Sample Fit Diagnostics for First Quarter Model (continued)

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
HSGC	CL	3714	0.1654	0.1715	0.0062	0.9639
	CO	3327	0.4189	0.3932	-0.0257	1.0653
	EL	2663	0.1330	0.1414	0.0084	0.9405
	FA	2937	0.1110	0.1187	0.0077	0.9355
	GM	2281	0.0620	0.0489	-0.0131	1.2676
	MM	3537	0.1463	0.1555	0.0092	0.9407
	OF	3385	0.0724	0.0908	0.0184	0.7974
	SC	80	0.3674	0.3696	0.0022	0.9940
	ST	3339	0.2574	0.2443	-0.0131	1.0534
	Non-Acc	5175	0.1495	0.1485	-0.0010	1.0065
HSG	CL	774	0.1409	0.1598	0.0188	0.8823
	CO	748	0.3562	0.3638	0.0076	0.9792
	EL	642	0.1326	0.1531	0.0205	0.8663
	FA	590	0.0643	0.0740	0.0098	0.8680
	GM	523	0.0436	0.0511	0.0075	0.8536
	MM	755	0.1070	0.0967	-0.0103	1.1060
	OF	739	0.0777	0.0599	-0.0177	1.2960
	SC	35	0.3930	0.4226	0.0296	0.9299
	ST	857	0.3360	0.3673	0.0313	0.9148
	Non-Acc	1224	0.2272	0.1867	-0.0405	1.2170
Senior	CL	1307	0.1702	0.1256	-0.0446	1.3547
	CO	1265	0.3945	0.3446	-0.0499	1.1448
	EL	1090	0.1087	0.1165	0.0078	0.9328
	FA	1123	0.0660	0.0700	0.0040	0.9430
	GM	750	0.0628	0.0489	-0.0139	1.2843
	MM	1205	0.1167	0.1414	0.0246	0.8258
	OF	1189	0.0595	0.0462	-0.0133	1.2890
	SC	121	0.3044	0.2047	-0.0997	1.4873
	ST	1342	0.2637	0.2504	-0.0134	1.0534
	Non-Acc	1998	0.2197	0.2868	0.0671	0.7662
NG	CL	814	0.1431	0.1578	0.0147	0.9067
	CO	1108	0.5690	0.5386	-0.0304	1.0564
	EL	687	0.1972	0.2144	0.0172	0.9199
	FA	746	0.2514	0.2385	-0.0129	1.0541
	GM	548	0.0449	0.0612	0.0163	0.7333
	MM	849	0.2375	0.2370	-0.0005	1.0020
	OF	765	0.1445	0.1224	-0.0221	1.1810
	SC	46	0.1172	0.0000	-0.1172	.
	ST	780	0.1951	0.1848	-0.0104	1.0562
	Non-Acc	1756	0.1131	0.1358	0.0227	0.8330

Table D.1. Out-of-Sample Fit Diagnostics for First Quarter Model (continued)

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
Cat1-3A	CL	4860	0.1230	0.1195	-0.0036	1.0299
	CO	5134	0.4192	0.3947	-0.0246	1.0622
	EL	4516	0.1376	0.1522	0.0146	0.9043
	FA	4286	0.1093	0.1070	-0.0023	1.0210
	GM	3365	0.0392	0.0368	-0.0024	1.0661
	MM	5004	0.1389	0.1374	-0.0015	1.0112
	OF	4713	0.0688	0.0665	-0.0023	1.0340
	SC	183	0.3358	0.3549	0.0191	0.9463
	ST	5216	0.2740	0.2644	-0.0095	1.0361
	Non-Acc	7603	0.1593	0.1799	0.0206	0.8855
Cat3B	CL	1743	0.2674	0.2736	0.0063	0.9771
	CO	1307	0.4838	0.4471	-0.0367	1.0822
	EL	564	0.1290	0.1116	-0.0174	1.1558
	FA	1104	0.1420	0.1719	0.0300	0.8257
	GM	733	0.1410	0.1157	-0.0253	1.2184
	MM	1334	0.1838	0.2301	0.0463	0.7989
	OF	1359	0.1186	0.1391	0.0206	0.8522
	SC	99	0.2462	0.0437	-0.2025	5.6324
	ST	1099	0.2032	0.2109	0.0077	0.9637
	Non-Acc	2540	0.1869	0.1682	-0.0187	1.1112
Cat4	CL	6	0.0545	0.0000	-0.0545	.
	CO	7	0.4397	0.1571	-0.2826	2.7989
	EL	2	0.0539	0.0000	-0.0539	.
	FA	6	0.2074	0.1815	-0.0259	1.1427
	GM	4	0.0736	0.0000	-0.0736	.
	MM	8	0.3158	0.2783	-0.0375	1.1349
	OF	6	0.0690	0.0000	-0.0690	.
	SC	.	.	.	.	.
	ST	3	0.0735	0.0000	-0.0735	.
	Non-Acc	10	0.1882	0.5624	0.3742	0.3346

Table D.2 Out-of-Sample Fit Diagnostics for Second Quarter Model

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
ALL	CL	11682	0.1985	0.1954	-0.0031	1.0159
	CO	11596	0.4279	0.3985	-0.0295	1.0739
	EL	9382	0.1405	0.1539	0.0134	0.9131
	FA	8652	0.1261	0.1307	0.0046	0.9648
	GM	5427	0.0426	0.0420	-0.0006	1.0136
	MM	10742	0.1456	0.1560	0.0103	0.9339
	OF	10100	0.0652	0.0666	0.0015	0.9782
	SC	767	0.1749	0.1892	0.0143	0.9242
	ST	11309	0.2543	0.2480	-0.0063	1.0255
	Non-Acc	17660	0.1471	0.1555	0.0084	0.9461
Multiple-Opp	CL	10900	0.1512	0.1471	-0.0041	1.0276
	CO	9539	0.3318	0.2945	-0.0373	1.1265
	EL	9192	0.1249	0.1384	0.0135	0.9027
	FA	8401	0.1024	0.1081	0.0057	0.9470
	GM	5357	0.0273	0.0259	-0.0014	1.0556
	MM	10491	0.1269	0.1365	0.0096	0.9300
	OF	9927	0.0504	0.0519	0.0014	0.9724
	SC	729	0.1387	0.1529	0.0142	0.9072
	ST	10267	0.1933	0.1874	-0.0060	1.0319
	Non-Acc	12806	0.1502	0.1636	0.0134	0.9184
Single-Opp	CL	782	0.8430	0.8528	0.0098	0.9885
	CO	2057	0.8784	0.8855	0.0071	0.9920
	EL	190	0.8439	0.8528	0.0089	0.9896
	FA	251	0.8706	0.8397	-0.0309	1.0368
	GM	70	0.8252	0.8691	0.0440	0.9494
	MM	251	0.8504	0.8888	0.0384	0.9568
	OF	173	0.8382	0.8407	0.0025	0.9971
	SC	38	0.8443	0.8615	0.0171	0.9801
	ST	1042	0.8527	0.8429	-0.0098	1.0116
	Non-Acc	4854	0.1391	0.1346	-0.0044	1.0329
Male	CL	9077	0.1464	0.1420	-0.0043	1.0305
	CO	10720	0.4610	0.4298	-0.0312	1.0726
	EL	7546	0.1391	0.1542	0.0151	0.9022
	FA	8464	0.1280	0.1328	0.0049	0.9635
	GM	3831	0.0502	0.0508	0.0006	0.9886
	MM	8676	0.1597	0.1661	0.0064	0.9612
	OF	8106	0.0562	0.0569	0.0007	0.9872
	SC	441	0.1751	0.2246	0.0495	0.7798
	ST	8840	0.2065	0.2078	0.0013	0.9939
	Non-Acc	14097	0.1303	0.1387	0.0084	0.9392
Female	CL	2605	0.3810	0.3822	0.0012	0.9969
	CO	876	0.0243	0.0161	-0.0082	1.5083
	EL	1836	0.1465	0.1528	0.0063	0.9586
	FA	188	0.0395	0.0326	-0.0070	1.2135
	GM	1596	0.0240	0.0206	-0.0034	1.1631
	MM	2066	0.0862	0.1129	0.0267	0.7638
	OF	1994	0.1022	0.1066	0.0044	0.9585
	SC	326	0.1745	0.1415	-0.0330	1.2333
	ST	2469	0.4268	0.3931	-0.0337	1.0858
	Non-Acc	3563	0.2140	0.2222	0.0082	0.9633

Table D.2 Out-of-Sample Fit Diagnostics for Second Quarter Model (continued)

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
HSGC	CL	6477	0.2044	0.2153	0.0109	0.9493
	CO	5960	0.4052	0.3780	-0.0272	1.0721
	EL	4875	0.1239	0.1415	0.0177	0.8753
	FA	4695	0.1319	0.1257	-0.0061	1.0487
	GM	3037	0.0436	0.0449	0.0013	0.9721
	MM	5782	0.1387	0.1501	0.0114	0.9240
	OF	5340	0.0665	0.0652	-0.0013	1.0192
	SC	233	0.2169	0.2792	0.0623	0.7768
	ST	6026	0.2355	0.2222	-0.0134	1.0601
	Non-Acc	8739	0.1218	0.1259	0.0041	0.9672
HSG	CL	1444	0.2015	0.1828	-0.0188	1.1027
	CO	1313	0.3668	0.3002	-0.0666	1.2217
	EL	1217	0.1524	0.1593	0.0069	0.9568
	FA	1024	0.0673	0.0879	0.0206	0.7658
	GM	730	0.0298	0.0351	0.0052	0.8510
	MM	1335	0.1269	0.0999	-0.0270	1.2699
	OF	1268	0.0642	0.0576	-0.0066	1.1146
	SC	71	0.2541	0.2734	0.0193	0.9293
	ST	1603	0.3447	0.3540	0.0093	0.9738
	Non-Acc	2171	0.1457	0.1955	0.0498	0.7454
Senior	CL	2498	0.2098	0.1688	-0.0411	1.2434
	CO	2455	0.3896	0.3530	-0.0366	1.1037
	EL	2113	0.1421	0.1348	-0.0073	1.0539
	FA	1770	0.0588	0.0879	0.0291	0.6692
	GM	1028	0.0516	0.0395	-0.0121	1.3061
	MM	2325	0.1206	0.1479	0.0273	0.8157
	OF	2311	0.0486	0.0508	0.0022	0.9565
	SC	377	0.1325	0.1459	0.0134	0.9081
	ST	2437	0.2327	0.2584	0.0257	0.9004
	Non-Acc	3773	0.2214	0.2300	0.0086	0.9628
NG	CL	1263	0.1435	0.1603	0.0169	0.8947
	CO	1868	0.5940	0.5929	-0.0011	1.0018
	EL	1177	0.1945	0.2331	0.0387	0.8342
	FA	1163	0.2547	0.2519	-0.0028	1.0111
	GM	632	0.0378	0.0403	0.0025	0.9384
	MM	1300	0.2390	0.2525	0.0135	0.9464
	OF	1181	0.0922	0.1129	0.0207	0.8163
	SC	86	0.1780	0.0623	-0.1157	2.8584
	ST	1243	0.2703	0.2161	-0.0542	1.2508
	Non-Acc	2977	0.1298	0.1204	-0.0095	1.0788

Table D.2 Out-of-Sample Fit Diagnostics for Second Quarter Model (continued)

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
Cat1-3A	CL	7980	0.1453	0.1345	-0.0108	1.0804
	CO	8591	0.3985	0.3749	-0.0236	1.0629
	EL	7806	0.1462	0.1630	0.0168	0.8972
	FA	6753	0.1163	0.1220	0.0058	0.9528
	GM	4208	0.0354	0.0349	-0.0005	1.0146
	MM	8219	0.1367	0.1409	0.0042	0.9699
	OF	7736	0.0538	0.0546	0.0007	0.9870
	SC	530	0.1857	0.2309	0.0452	0.8044
	ST	8947	0.2640	0.2612	-0.0027	1.0105
	Non-Acc	12511	0.1544	0.1608	0.0064	0.9603
Cat3B	CL	3571	0.3121	0.3238	0.0117	0.9638
	CO	2868	0.5052	0.4528	-0.0524	1.1156
	EL	1548	0.1133	0.1107	-0.0026	1.0234
	FA	1857	0.1581	0.1575	-0.0006	1.0038
	GM	1164	0.0645	0.0692	0.0047	0.9322
	MM	2448	0.1737	0.2041	0.0305	0.8509
	OF	2272	0.0996	0.1080	0.0085	0.9217
	SC	233	0.1525	0.0976	-0.0549	1.5628
	ST	2337	0.2183	0.1989	-0.0194	1.0975
	Non-Acc	4927	0.1300	0.1445	0.0145	0.8997
Cat4	CL	131	0.3780	0.4439	0.0659	0.8515
	CO	137	0.6676	0.7484	0.0808	0.8920
	EL	28	0.0549	0.0000	-0.0549	.
	FA	42	0.2875	0.3361	0.0486	0.8554
	GM	55	0.1366	0.0192	-0.1174	7.1342
	MM	75	0.2135	0.2343	0.0207	0.9115
	OF	92	0.1772	0.0683	-0.1089	2.5942
	SC	4	0.0342	0.0000	-0.0342	.
	ST	25	0.1225	0.0404	-0.0822	3.0348
	Non-Acc	222	0.1130	0.0992	-0.0139	1.1401

Table D.3. Out-of-Sample Fit Diagnostics for Third Quarter Model

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
ALL	CL	13751	0.2232	0.2179	-0.0053	1.0245
	CO	10001	0.3935	0.3637	-0.0297	1.0818
	EL	9611	0.1493	0.1632	0.0139	0.9147
	FA	9837	0.1353	0.1456	0.0102	0.9297
	GM	6739	0.0404	0.0359	-0.0045	1.1240
	MM	12651	0.1826	0.1836	0.0010	0.9946
	OF	12591	0.1072	0.1073	0.0001	0.9991
	SC	533	0.1898	0.1802	-0.0096	1.0534
	ST	11750	0.2664	0.2477	-0.0188	1.0757
	Non-Acc	19868	0.1507	0.1697	0.0191	0.8877
Multiple-Opp	CL	12827	0.1771	0.1723	-0.0048	1.0277
	CO	8587	0.3071	0.2738	-0.0334	1.1218
	EL	9445	0.1362	0.1506	0.0144	0.9042
	FA	9641	0.1208	0.1309	0.0102	0.9223
	GM	6677	0.0289	0.0237	-0.0053	1.2232
	MM	12325	0.1646	0.1660	0.0014	0.9914
	OF	12242	0.0862	0.0863	0.0001	0.9990
	SC	511	0.1544	0.1468	-0.0076	1.0520
	ST	10729	0.2075	0.1909	-0.0166	1.0871
	Non-Acc	15388	0.1568	0.1772	0.0204	0.8851
Single-Opp	CL	924	0.8531	0.8401	-0.0130	1.0154
	CO	1414	0.8935	0.8847	-0.0088	1.0100
	EL	166	0.8572	0.8442	-0.0130	1.0154
	FA	196	0.8680	0.8811	0.0131	0.9851
	GM	62	0.8658	0.9211	0.0553	0.9400
	MM	326	0.8486	0.8337	-0.0149	1.0179
	OF	349	0.8449	0.8451	0.0002	0.9998
	SC	22	0.8780	0.8298	-0.0482	1.0581
	ST	1021	0.8682	0.8278	-0.0404	1.0489
	Non-Acc	4480	0.1303	0.1451	0.0148	0.8982
Male	CL	10812	0.1794	0.1715	-0.0078	1.0457
	CO	9780	0.4014	0.3709	-0.0305	1.0823
	EL	7308	0.1458	0.1608	0.0150	0.9068
	FA	9697	0.1370	0.1477	0.0107	0.9279
	GM	4814	0.0488	0.0425	-0.0063	1.1480
	MM	10144	0.1933	0.1961	0.0028	0.9857
	OF	10224	0.0985	0.1015	0.0031	0.9699
	SC	371	0.1343	0.1486	0.0143	0.9039
	ST	9131	0.2268	0.2078	-0.0190	1.0914
	Non-Acc	15621	0.1337	0.1536	0.0198	0.8709
Female	CL	2939	0.3850	0.3889	0.0039	0.9900
	CO	221	0.0531	0.0577	0.0046	0.9201
	EL	2303	0.1605	0.1710	0.0105	0.9385
	FA	140	0.0184	0.0000	-0.0184	.
	GM	1925	0.0189	0.0191	0.0002	0.9886
	MM	2507	0.1392	0.1328	-0.0064	1.0482
	OF	2367	0.1453	0.1325	-0.0128	1.0968
	SC	162	0.3150	0.2515	-0.0635	1.2526
	ST	2619	0.4048	0.3868	-0.0179	1.0463
	Non-Acc	4247	0.2132	0.2295	0.0163	0.9291

Table D.3. Out-of-Sample Fit Diagnostics for Third Quarter Model (continued)

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
HSGC	CL	6831	0.2461	0.2426	-0.0034	1.0142
	CO	4567	0.3587	0.3388	-0.0199	1.0587
	EL	4419	0.1478	0.1598	0.0120	0.9250
	FA	4704	0.1291	0.1450	0.0159	0.8901
	GM	3331	0.0415	0.0407	-0.0008	1.0192
	MM	6030	0.1888	0.1858	-0.0029	1.0158
	OF	6168	0.1117	0.1124	0.0007	0.9940
	SC	287	0.1798	0.1539	-0.0259	1.1680
	ST	5360	0.2746	0.2477	-0.0269	1.1087
	Non-Acc	9296	0.1350	0.1516	0.0166	0.8904
HSG	CL	1689	0.2417	0.2246	-0.0171	1.0763
	CO	1172	0.3857	0.3446	-0.0412	1.1195
	EL	1251	0.1652	0.1814	0.0162	0.9108
	FA	1130	0.1035	0.0920	-0.0115	1.1252
	GM	914	0.0246	0.0195	-0.0051	1.2594
	MM	1567	0.0923	0.1027	0.0104	0.8989
	OF	1523	0.0857	0.0567	-0.0290	1.5113
	SC	60	0.2632	0.2736	0.0104	0.9619
	ST	1703	0.3767	0.3496	-0.0271	1.0776
	Non-Acc	2480	0.1457	0.2049	0.0591	0.7113
Senior	CL	2941	0.2069	0.1911	-0.0158	1.0827
	CO	2574	0.4330	0.3800	-0.0530	1.1396
	EL	2319	0.1443	0.1725	0.0282	0.8365
	FA	2042	0.0745	0.0788	0.0043	0.9458
	GM	1403	0.0407	0.0282	-0.0125	1.4437
	MM	2680	0.1468	0.1565	0.0097	0.9379
	OF	2625	0.0819	0.0730	-0.0089	1.1215
	SC	68	0.2659	0.3984	0.1325	0.6675
	ST	2673	0.2425	0.2316	-0.0109	1.0469
	Non-Acc	4334	0.1848	0.2179	0.0331	0.8482
NG	CL	2290	0.1622	0.1733	0.0111	0.9361
	CO	1688	0.4330	0.4196	-0.0134	1.0319
	EL	1622	0.1483	0.1455	-0.0028	1.0194
	FA	1961	0.2315	0.2467	0.0152	0.9385
	GM	1091	0.0494	0.0445	-0.0049	1.1106
	MM	2374	0.2660	0.2611	-0.0049	1.0188
	OF	2275	0.1383	0.1663	0.0280	0.8316
	SC	118	0.1290	0.0629	-0.0661	2.0507
	ST	2014	0.1828	0.1825	-0.0003	1.0014
	Non-Acc	3758	0.1536	0.1362	-0.0175	1.1281

Table D.3. Out-of-Sample Fit Diagnostics for Third Quarter Model (continued)

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
Cat1-3A	CL	9138	0.1648	0.1592	-0.0057	1.0357
	CO	6839	0.3757	0.3369	-0.0388	1.1151
	EL	7858	0.1515	0.1675	0.0160	0.9047
	FA	7438	0.1175	0.1295	0.0120	0.9073
	GM	5349	0.0326	0.0283	-0.0043	1.1517
	MM	9569	0.1516	0.1599	0.0083	0.9482
	OF	9093	0.0862	0.0819	-0.0043	1.0521
	SC	255	0.2779	0.3126	0.0347	0.8889
	ST	9416	0.2833	0.2580	-0.0254	1.0983
	Non-Acc	13220	0.1508	0.1746	0.0238	0.8638
Cat3B	CL	4292	0.3394	0.3335	-0.0059	1.0176
	CO	2849	0.4165	0.3972	-0.0193	1.0485
	EL	1672	0.1418	0.1493	0.0075	0.9500
	FA	2307	0.1917	0.1937	0.0021	0.9893
	GM	1225	0.0658	0.0671	0.0013	0.9800
	MM	2855	0.2719	0.2546	-0.0174	1.0681
	OF	3196	0.1563	0.1691	0.0129	0.9238
	SC	255	0.1117	0.0637	-0.0481	1.7551
	ST	2267	0.1970	0.2047	0.0078	0.9621
	Non-Acc	6073	0.1524	0.1632	0.0108	0.9341
Cat4	CL	321	0.3475	0.3595	0.0119	0.9669
	CO	313	0.5695	0.6404	0.0709	0.8893
	EL	81	0.0874	0.0358	-0.0516	2.4416
	FA	92	0.1749	0.2462	0.0713	0.7104
	GM	165	0.1044	0.0520	-0.0524	2.0069
	MM	227	0.3780	0.3008	-0.0772	1.2566
	OF	302	0.2292	0.2266	-0.0026	1.0114
	SC	23	0.0758	0.0000	-0.0758	.
	ST	67	0.2152	0.2377	0.0225	0.9053
	Non-Acc	575	0.1295	0.1271	-0.0024	1.0186

Table D.4. Out-of-Sample Fit Diagnostics for Fourth Quarter Model

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
ALL	CL	18222	0.2081	0.2101	0.0020	0.9906
	CO	17542	0.3867	0.3525	-0.0342	1.0970
	EL	14903	0.1280	0.1343	0.0064	0.9524
	FA	14410	0.0996	0.0995	-0.0001	1.0006
	GM	13326	0.0351	0.0360	0.0009	0.9757
	MM	17898	0.1535	0.1619	0.0084	0.9481
	OF	17408	0.0862	0.0849	-0.0013	1.0156
	SC	2799	0.1904	0.1884	-0.0019	1.0103
	ST	19047	0.2857	0.2717	-0.0140	1.0515
	Non-Acc	27982	0.1197	0.1413	0.0215	0.8475
Multiple-Opp	CL	17298	0.1720	0.1750	0.0030	0.9828
	CO	15506	0.3139	0.2802	-0.0337	1.1204
	EL	14629	0.1142	0.1207	0.0065	0.9460
	FA	14243	0.0903	0.0900	-0.0003	1.0034
	GM	13217	0.0283	0.0286	0.0004	0.9878
	MM	17551	0.1399	0.1482	0.0083	0.9441
	OF	17058	0.0709	0.0693	-0.0015	1.0222
	SC	2719	0.1684	0.1676	-0.0008	1.0048
	ST	17579	0.2346	0.2230	-0.0116	1.0519
	Non-Acc	22227	0.1254	0.1461	0.0208	0.8578
Single-Opp	CL	924	0.8863	0.8686	-0.0177	1.0203
	CO	2036	0.9379	0.9003	-0.0376	1.0418
	EL	274	0.8684	0.8681	-0.0003	1.0004
	FA	167	0.8604	0.8806	0.0202	0.9771
	GM	109	0.7791	0.8371	0.0580	0.9307
	MM	347	0.8330	0.8466	0.0136	0.9840
	OF	350	0.8387	0.8477	0.0090	0.9893
	SC	80	0.9449	0.9043	-0.0406	1.0449
	ST	1468	0.9129	0.8694	-0.0436	1.0501
	Non-Acc	5755	0.0979	0.1224	0.0245	0.8002
Male	CL	14304	0.1495	0.1425	-0.0070	1.0490
	CO	16245	0.4152	0.3784	-0.0368	1.0971
	EL	11863	0.1304	0.1382	0.0078	0.9434
	FA	13910	0.1027	0.1025	-0.0002	1.0022
	GM	10088	0.0338	0.0341	0.0004	0.9895
	MM	14500	0.1644	0.1754	0.0110	0.9373
	OF	13939	0.0693	0.0716	0.0022	0.9687
	SC	1668	0.1703	0.2094	0.0391	0.8131
	ST	14647	0.2342	0.2190	-0.0153	1.0697
	Non-Acc	21675	0.1106	0.1370	0.0263	0.8077
Female	CL	3918	0.4231	0.4580	0.0349	0.9239
	CO	1297	0.0286	0.0265	-0.0020	1.0770
	EL	3040	0.1185	0.1192	0.0008	0.9936
	FA	500	0.0119	0.0166	0.0046	0.7205
	GM	3238	0.0393	0.0418	0.0025	0.9403
	MM	3398	0.1065	0.1037	-0.0028	1.0270
	OF	3469	0.1543	0.1386	-0.0157	1.1135
	SC	1131	0.2201	0.1574	-0.0626	1.3978
	ST	4400	0.4580	0.4483	-0.0098	1.0218
	Non-Acc	6307	0.1511	0.1561	0.0050	0.9682

Table D.4. Out-of-Sample Fit Diagnostics for Fourth Quarter Model(continued)

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
HSGC	CL	9720	0.2262	0.2324	0.0062	0.9733
	CO	9158	0.3672	0.3146	-0.0526	1.1670
	EL	7338	0.1107	0.1298	0.0191	0.8532
	FA	7912	0.1068	0.1079	0.0011	0.9896
	GM	7507	0.0378	0.0403	0.0024	0.9394
	MM	9418	0.1569	0.1674	0.0105	0.9372
	OF	9194	0.0921	0.0930	0.0009	0.9904
	SC	1356	0.2012	0.2033	0.0021	0.9897
	ST	9996	0.2886	0.2576	-0.0311	1.1205
	Non-Acc	14696	0.1156	0.1465	0.0309	0.7894
HSG	CL	1933	0.2390	0.2184	-0.0207	1.0947
	CO	1771	0.3592	0.3005	-0.0587	1.1952
	EL	1637	0.1037	0.1192	0.0154	0.8705
	FA	1516	0.0452	0.0671	0.0219	0.6736
	GM	1503	0.0151	0.0215	0.0064	0.7013
	MM	1923	0.0872	0.0994	0.0122	0.8769
	OF	1780	0.0669	0.0591	-0.0079	1.1337
	SC	253	0.2772	0.2250	-0.0522	1.2319
	ST	2400	0.3892	0.3856	-0.0036	1.0093
	Non-Acc	3119	0.1504	0.1787	0.0283	0.8417
Senior	CL	5254	0.1808	0.1805	-0.0003	1.0015
	CO	5060	0.4205	0.4150	-0.0055	1.0132
	EL	4626	0.1401	0.1338	-0.0063	1.0471
	FA	3800	0.0873	0.0715	-0.0158	1.2207
	GM	3330	0.0426	0.0338	-0.0088	1.2595
	MM	5116	0.1584	0.1626	0.0042	0.9742
	OF	5105	0.0739	0.0709	-0.0030	1.0426
	SC	1028	0.1603	0.1799	0.0196	0.8912
	ST	5225	0.2743	0.2732	-0.0011	1.0041
	Non-Acc	7732	0.0958	0.1123	0.0165	0.8531
NG	CL	1315	0.1387	0.1515	0.0128	0.9156
	CO	1553	0.4225	0.4303	0.0078	0.9818
	EL	1302	0.2120	0.1809	-0.0312	1.1723
	FA	1182	0.1599	0.1745	0.0146	0.9164
	GM	986	0.0198	0.0329	0.0131	0.6010
	MM	1441	0.2018	0.2061	0.0044	0.9788
	OF	1329	0.1182	0.1169	-0.0014	1.0116
	SC	162	0.1553	0.0614	-0.0939	2.5304
	ST	1426	0.1344	0.1750	0.0406	0.7679
	Non-Acc	2435	0.1813	0.1541	-0.0271	1.1761

Table D.4. Out-of-Sample Fit Diagnostics for Fourth Quarter Model(continued)

Subgroup	Job Family	Freq	Estimate (E)	Actual (A)	Diff (A-E)	Ratio (E/A)
Cat1-3A	CL	12897	0.1500	0.1460	-0.0040	1.0273
	CO	12511	0.3553	0.3380	-0.0173	1.0512
	EL	12293	0.1267	0.1343	0.0075	0.9440
	FA	11190	0.0954	0.0940	-0.0014	1.0153
	GM	10193	0.0289	0.0277	-0.0012	1.0425
	MM	13855	0.1357	0.1335	-0.0023	1.0168
	OF	12753	0.0683	0.0616	-0.0067	1.1084
	SC	1821	0.2265	0.2315	0.0051	0.9782
	ST	15353	0.3055	0.2891	-0.0164	1.0568
	Non-Acc	19476	0.1188	0.1477	0.0289	0.8043
Cat3B	CL	5305	0.3476	0.3635	0.0159	0.9562
	CO	5013	0.4634	0.3877	-0.0758	1.1955
	EL	2607	0.1337	0.1349	0.0012	0.9909
	FA	3214	0.1136	0.1184	0.0048	0.9595
	GM	3128	0.0553	0.0629	0.0076	0.8798
	MM	4034	0.2134	0.2583	0.0449	0.8263
	OF	4640	0.1346	0.1478	0.0132	0.9109
	SC	975	0.1237	0.1091	-0.0146	1.1338
	ST	3687	0.2041	0.2002	-0.0039	1.0194
	Non-Acc	8467	0.1220	0.1266	0.0046	0.9637
Cat4	CL	20	0.5710	0.7006	0.1296	0.8150
	CO	18	0.7127	0.5720	-0.1407	1.2459
	EL	3	0.0840	0.0000	-0.0840	.
	FA	6	0.2327	0.1691	-0.0637	1.3765
	GM	5	0.0330	0.0000	-0.0330	.
	MM	9	0.3412	0.2230	-0.1182	1.5303
	OF	15	0.2815	0.3363	0.0548	0.8370
	SC	3	0.1057	0.0000	-0.1057	.
	ST	7	0.1737	0.1422	-0.0316	1.2220
	Non-Acc	39	0.1066	0.1467	0.0401	0.7268